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IDENTIFICATION OF CUTTING CHATTER THROUGH DEEP LEARNING AND CLASSIFICATION

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Abstract
The traditional analytical method has difficulty in accurately modelling cutting chatter. This paper constructs the vibration datasets of different chatter states and establishes a machine learning (ML) model for chatter identification, treating physical vibration signal as the input. Specifically, the cutting vibration signal was converted into the time-frequency spectrum, which was then classified by a self-designed deep residual convolutional neural network (DR-CNN). After that, the cutting vibration signal was broken down into chatter bands through variational mode decomposition (VMD). The information entropies of the chatter bands were calculated as cutting chatter features. Next, support vector machine (SVM) was introduced to classify the extracted features and used to create an online cutting chatter identification algorithm. The proposed method achieved a much higher mean identification accuracy (92.57 %) than the traditional identification method.
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Key Words: Cutting Chatter, Chatter Identification, Deep Residual Convolutional Neural Network (DR-CNN), Support Vector Machine (SVM), Variational Mode Decomposition (VMD)

1. INTRODUCTION

The application of cutter improves the automation level and reduces the cost of manufacturing. However, the weak rigidity of the cutter often brings vibration, especially chatter, in the cutting process, which in turn hampers the quality and efficiency of cutting.

Many vibration avoidance or suppression strategies have been developed to predict or identify chatter in cutting process, aiming to improve the cutting efficiency and surface quality of workpiece, and prevent damages to the cutting system.

Nevertheless, the traditional analytical method has difficulty in accurately modelling cutting chatter, because the dynamic features of cutter, unlike those of traditional machine tools, are affected by the dynamic features of the machine.

The cutting quality and efficiency can be characterized by various indices, such as current, vibration, force, and the surface condition of the workpiece. The data on these indices should be processed and imported to machine learning (ML) [1-4] model to mine the cutting rules. The rules can be networked with the data to realize collaborative manufacturing.

Aiming to identify cutting chatter, this paper learns the mapping between vibration signals of different chatter states by data-driven method and derives the chatter state in the cutting process directly from the physical signal of the cutting system.

2. LITERATURE REVIEW

Cutting chatter is generally analysed by analytical method or data-driven method. The former method first models and examines the dynamic features of the cutting system, determines the force, heat, and transfer function of the system, and substitutes these parameters into the dynamic equation to solve the cutting chatter. The latter method collects the signals of cutting vibration, current, force, and sound into a labelled sample set of cutting big data, trains the black box model to learn the mapping between input and output parameters, and directly predict the cutting chatter based on the physical signal.

Cutting vibration can be roughly divided into free vibration, forced vibration, and chatter. The last type of cutting vibration is the focus of this research. Altintas et al. [5] designed a five-axis cutting chatter stability model, solved the model by frequency domain method, and analysed the stability impact of forward tilt and roll angle. Considering the variation of cutter axis vector, Eynian and Altintas [6] established a five-axis cutting chatter stability model and presented the attitude calculation method corresponding to the fixed limit cutting depth. Shaik and Srinivas [7] modelled the chatter stability of the ring cutter in compound cutting of turn miller and predicted chatter stability more accurately in the light of the stability impacts from multi-modal and cross frequency responses.

The solution of stability model has been explored by quite a few scholars. Song et al. [8] proposed a fully discrete method that derives the eigenvalues of the system transfer matrix in a single cutting cycle under the Floquet criterion, and then gives the stability criterion. Chen et al. [9] developed a linear accelerated stability solution model, which speeds up the full discrete method by reducing the scale of the state transition matrix. Based on Simpson method, Graham et al. [10] presented a numerical method to solve the stability model: the calculation speed of the full discrete method was further improved by eliminating the discrete delay term.

Compared with the traditional analytical method, machine learning (ML) [11] can learn the mapping between input and output from real data samples (e.g., vibration signal), thereby improving the prediction accuracy of cutting chatter. Yang et al. [12] determined cutting chatter by normalized Kolmogorov-Sinai (K-S) entropy of vibration signal and made quick predictions of chatter occurrence. Ertunc et al. [13] extracted the chatter features of cutting force signals through spectrum estimation by estimation of signal parameters via rotational invariance techniques (ESPRIT), which works well on a small number of single samples and identified chatter with hidden Markov model. Focusing on the milling chatter of machine tools, Ramesh et al. [14] extracted sample features through variational mode decomposition (VMD) and classified the samples with the probabilistic neural network. Wu et al. [15] combined the support vector machine (SVM) [16, 17] with backpropagation neural network (BPNN) [18, 19] to predict milling stability, and proved that the combined approach outperformed the traditional analytical method in prediction accuracy. Through kernel principal component analysis (KPCA), Chiou and Liang [20] fused multi-sensor signals of milling force and vibration and imported the extracted features into support vector regression (SVR) model for cutter wear forecast. Han et al. [21] extracted force and vibration features with discrete wavelet, creatively trained the SVM with cutting parameters, and achieved excellent results on chatter identification. Siddhpura and Paurobally [22] demonstrated that fast Fourier transform (FFT) on VMD signals can improve the identification of milling chatter frequency band and facilitate the further extraction of chatter features.

3. DEEP LEARNING (DL)-BASED OFFLINE CUTTING CHATTER IDENTIFICATION

3.1 Features of cutting chatter

According to the classical theory on regenerative chatter, the dynamic equation of cutter end can be established through analytical modelling, and the chatter stability can be predicted by time domain method.

In this paper, the original data are acquired from the industrial milling platform ABB IRB6600, which has a circular disc cutter. The vibration was captured by one-way acceleration sensor, frequency response was collected by Vib Runner vibration acquisition platform, and modal parameters were obtained by Smart Office.

The relevant data were collected through 10 hammering tests in the X and Y directions of the cutter tip. Then, the frequency response data were analysed on Smart Office. Through the analysis, the authors fitted the frequency response functions in the two directions, and determined modal parameters, including modal mass, damping ratio, and natural frequency. The modal parameters in X and Y directions are listed in Table I.

Table I: The modal parameters in X and Y directions.

Frequency response function	**Modal mass** (kg)	**Damping ratio**	**Natural frequency**
GX	0.972	5.232 %	881.701
GY	1.168	3.579 %	921.728

As shown in Fig. 1, the milling platform can be simplified into a two-degree-of-freedom (2DOF) dynamic system composed of mass, damper, and spring.

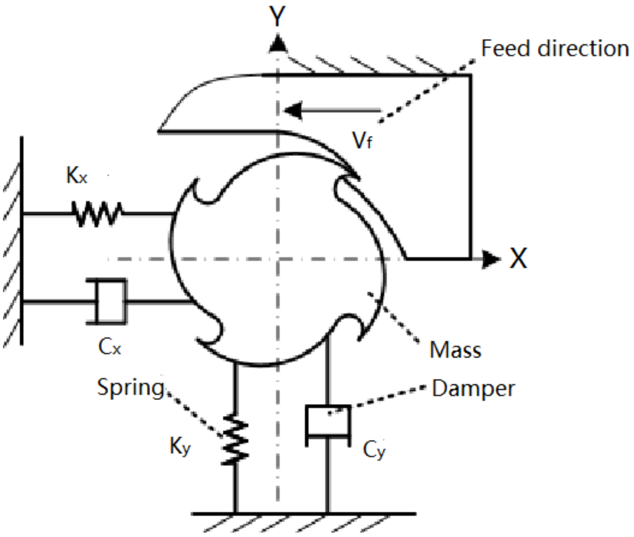


Figure 1: The 2DOF dynamic system.

The dynamic equation of the 2DOF dynamic system can be expressed as:

$$\mathrm{M}\begin{bmatrix}\ddot{x}(t)\\ \ddot{y}(t)\end{bmatrix}+D\begin{bmatrix}\dot{x}(t)\\ \dot{y}(t)\end{bmatrix}+W\begin{bmatrix}x(t)\\ y(t)\end{bmatrix}=W_c\begin{bmatrix}x(t)-x(t-T)\\ y(t)-y(t-T)\end{bmatrix} \tag{1}$$

where, M is modal mass matrix; D is damping matrix; W is stiffness matrix; W_c is cutting force coefficient matrix; t and T are the current time and the cutting cycle, respectively; $x(t)-x(t–T)$ and $y(t)-y(t–T)$ are the dynamic cutting thicknesses in X and Y directions, respectively. The current cutting parameters were obtained by solving the dynamic equation.

After analysing the cutter end frequency response of the milling platform, it is learned that the dynamic features of the platform changed slightly in a limited range in the plane area of 80 mm × 160 mm. In this research, the cutting plane of the workpiece is 70 mm × 110 mm, and the single cutting range is 10 mm × 2170 mm. Therefore, it is assumed that the cutter can maintain the same vibration state, when it moves cyclically in a small range, as long as the cutting parameters remain unchanged. Hence, the chatter state of the cutter can be characterized by the vibration data of multiple cycles. That is, the vibration data under the same cutting parameters can represent the same chatter state. Fig. 2 shows the surface texture of the workpiece under the same cutting parameters.

In order to facilitate the training of the identification model, the vibration signal under the same cutting parameters were sampled with sliding windows, forming a standard vibration dataset under the same chatter state.

Figure 2: The surface texture of the workpiece under the same cutting parameters.

$$S_{ij} = S_i[1 + j \times S_{len}, f_s + j \times S_{len}] \quad (2)$$

where, S_{ij} is the j^{th} sample in the vibration signal of the i^{th} group of cutting parameters; j is the serial number of sliding window; f_s is the sampling frequency of the original vibration data; S_{len} is the step size of sliding window.

Based on the vibration ripples on the workpiece, four vibration states can be identified in the cutting process: stable state, transition state, regular chatter state, and irregular chatter state. Table II shows the proportion of each state observed in the cutting process.

Table II: The proportion of each vibration state in the cutting process.

Type	**Proportion**
Stable state	27.85 %
Transition state	15.25 %
Regular chatter state	27.35 %
Irregular chatter state	29.55 %

Next, the different types of vibration signals were analysed by FFT. The results show that: In the stable state, there was a single frequency component, which only covers the spindle rotation frequency and its multiple frequency; In the transition state, a small amount of weak harmonic frequency existed, apart from the spindle rotation frequency and its multiple frequency; In the regular chatter state, the chatter frequency beyond the doubling frequency appeared, which conforms to the classical criteria for regenerative chatter; In the irregular chatter state, the turn frequency and its double frequency were replaced by other harmonic frequencies.

From the time-frequency spectrum of wavelet, it can be seen that: In the stable state, the frequency component was time invariant, each frequency band was continuous, and the workpiece was smooth on the surface; In the transition state, most frequency components remained unchanged, a few frequency bands became discontinuous, and a small number of indistinct vibration patterns appeared on the workpiece; In the regular chatter state, there were a small amount of time-varying frequency components, some intermittent frequency bands, and obvious regular vibration patterns on the workpiece; In the irregular chatter state, many frequency components varied with time, virtually no frequency band was continuous, and the workpiece surface exhibited obvious irregular vibration patterns. Therefore, wavelet analysis can effectively capture the time-varying chatter components in the cutting process.

3.2 Chatter spectrum

Here, the cutting chatter signal is transformed into frequency spectrum through continuous wavelet transform (CWT) and VMD. In this way, the chatter identification is converted into the classification of images.

The previous analysis confirms that the wavelet time-frequency spectrum can effectively capture the time-varying chatter components in the cutting process. This means the chatter state of the cutting process can be characterized by the time-frequency spectrum of the vibration signal. The CWT can process the frequency components of signals in different time windows with different resolutions, and thus capture the time-frequency information of signals. This technique can retain more information of the original signal than traditional methods of time-frequency and frequency-domain analyses. The basic formula of the CWT can be defined as:

$$CWT_x(u,v) = |u|^{-1/2} \int x(t)\overline{\varphi}(t - v/u)dt \tag{3}$$

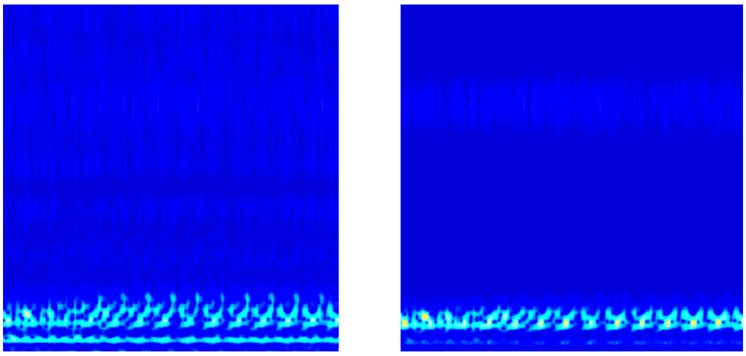
where, $\overline{\varphi}()$ is the wavelet function; u is the scale factor; v is the scaling factor; x is the original signal.

Before drawing the time spectrum through CWT, it is necessary to specify different wavelet functions and decomposition scales. Complex Morlet wavelet [23] was selected as the wavelet function:

$$\varphi_x = 1/\sqrt{f_B\pi}\, exp\,(-x^2/2 + j \times f_C 2\pi x) \tag{4}$$

where, f_B is bandwidth; f_c is centre frequency.

To mirror the chatter state, the vibration signal should only contain the frequency components related to the chatter frequency band. In other words, the irrelevant components like weakly correlated or uncorrelated frequency components (e.g., noise component and non-noise component generated during signal acquisition) must be eliminated before identifying the chatter state.



a) Before denoising b) After denoising

Figure 3: The comparison of the results before and after denoising.

For this purpose, the Lagrange multiplier of the VMD algorithm was weakened, ensuring that the reconstructed signal only retains the frequency components related to the eigenmode, i.e., the noise and weakly correlated components are removed from the signal. This treatment lays a solid basis for accurate feature discrimination of time-frequency spectrum.

Firstly, the VMD algorithm was called to pre-process the vibration signal, and then the CWT was performed to obtain the time-frequency spectrum of the vibration signal. Fig. 3 compares the results before and after denoising.

3.3 DR-CNN-based chatter identification

Previous studies have shown that the ability of a neural network to extract and represent features increases with its depth. However, if the neural network is excessively deep, the problem of vanishing gradients will occur, depriving the network of the mapping ability.

By introducing the residual unit module, the DR-CNN [24] can greatly improve the network depth, while preventing the problem of vanishing gradients. Hence, this neural network was adopted to identify the time-frequency spectrum of the vibration signal in cutting process.

The residual unit module is composed of a two-layer CNN on the left, and an identity map on the right. The input is linearly superimposed on the output of the second convolutional layer to activate the output. Here, an 18-layer ResNet-18 is adopted, and the input time-frequency spectrum is of the size 256 × 256. Table III and Fig. 4 display the test accuracies of the network under different decomposition levels.

Table III: The test accuracies under different decomposition levels.

Test result	**Decomposition levels**					
	5	6	7	8	9	10
Highest accuracy	0.9328	0.9462	0.9372	0.9458	0.9451	0.9482
Mean accuracy	0.9251	0.9335	0.9339	0.9425	0.9442	0.9437
Standard deviation	0.31 %	0.45 %	0.19 %	0.23 %	0.12 %	0.68 %

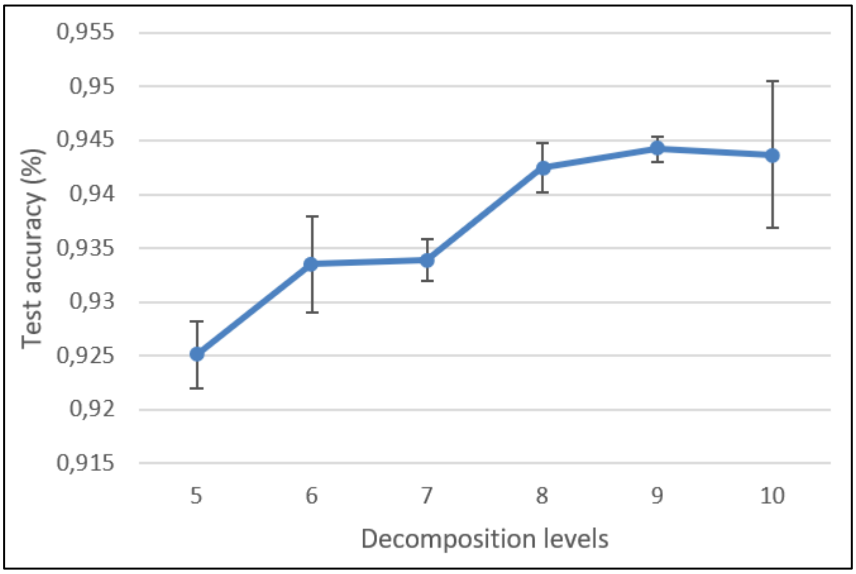


Figure 4: The influence of decomposition level on test accuracy.

As shown in Fig. 4, with the growing number n of decomposition layers, the prediction accuracy of the network first increased and then decreased. The prediction accuracy peaked at $n = 9$ and minimized at $n = 5$. Therefore, if the time spectrum is generated through the CWT, the accuracy of the network will increase with the number of decomposition levels. From the perspective of image processing, the addition of decomposition levels improves the resolution of the time-frequency spectrum, making the network more accurate in prediction.

Next, the influence of input normalization on prediction accuracy was analysed. Input normalization means transforming the input sample vector into a standard normal distribution through nondimensionalization. Previous studies [25, 26] have proved that input normalization can speed up network training and improve prediction accuracy. Table IV and Fig. 5 present the test accuracies under different decomposition levels after input normalization.

Table IV: The test accuracies under different decomposition levels after input normalization.

Test result	**Decomposition levels**					
	5	6	7	8	9	10
Highest accuracy	0.9385	0.9409	0.9435	0.9511	0.9518	0.9537
Mean accuracy	0.9322	0.9365	0.9403	0.9472	0.9476	0.9491
Standard deviation	0.33 %	0.27 %	0.31 %	0.35 %	0.16 %	0.26 %

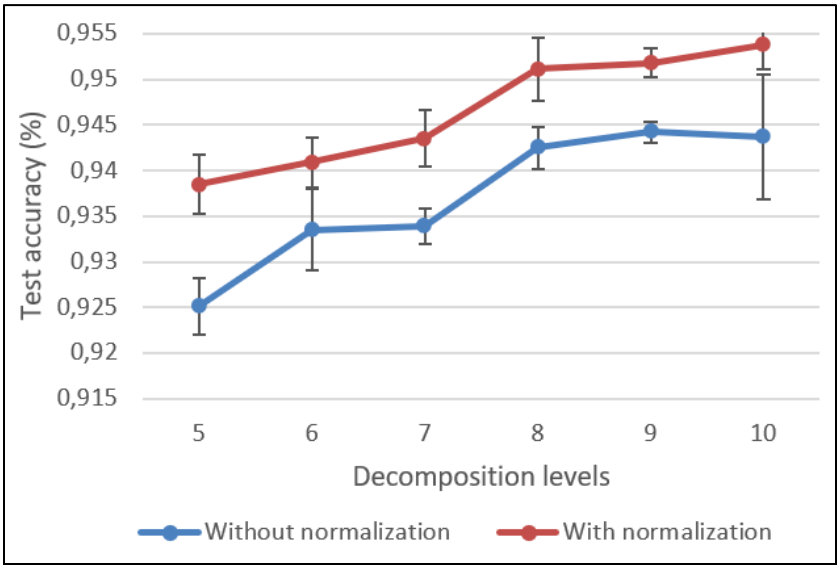


Figure 5: The influence of input normalization on test accuracy.

As shown in Fig. 5, the prediction accuracy was improved after input normalization. The results in Fig. 5 also reflect the rising trend of prediction accuracy, along with the growing number of decomposition levels.

The above operation is comparable to data enhancement in traditional image processing: The classification robustness is enhanced by injecting noise into the original image, such that the classification algorithm can produce stable output, even if the input contains a small disturbance. Unlike the traditional denoising method, this paper introduces the actual noise, which is produced by processing the original signal and the frequency component unrelated to chatter features. By contrast, the traditional method tends to inject Gaussian white noise to the original signal. As a result, the VMD can be adopted to improve the identification accuracy of cutting chatter.

4. SVM-BASED ONLINE CUTTING CHATTER IDENTIFICATION

The ML-based identification requires an artificial feature extraction algorithm. On the contrary, the DL can extract features automatically, and incur a small computing load, providing a satisfactory tool for online identification of cutting chatter.

Based on the VMD, this section presents a new feature extraction method of cutting vibration signal and sets up the feature sample set. Then, the feature sample set was imported to the SVM for training, creating an online cutting chatter identification algorithm.

Through the VMD, a finite number of sub-modal signals were extracted from the original signal. These sub-modal signals differ in centre frequency and have limited bandwidth in the frequency domain. The decomposition, which aims to minimize the sum of the estimated bandwidths of the sub-modal signals, was completed by solving each sub-modal signal and its centre frequency. The specific process is as follows:

Firstly, intrinsic mode function was defined as an amplitude modulation-frequency modulation (AM-FM) signal:

$$w_k(t) = B_k(t) cos\,(\gamma_k(t)) \tag{5}$$

where, $B_k(t)$ is instantaneous amplitude; $\gamma_k(t)$ is phase; k is modal number.

For a single intrinsic mode function, $W_k(t)$ was modulated to the fundamental frequency band at the estimated centre frequency, using Hilbert transform and exponential term. Then, an analytical signal S_k was obtained as:

$$S_k = [(\varepsilon(t) + j/\pi t) \times w_k(t)]\mathrm{e}^{-j\omega_k(t)t} \tag{6}$$

where, $\omega_k(t) = r_k'(t)$ is the instantaneous frequency of $W_k(t)$.

The estimated bandwidth of a single intrinsic mode function was obtained with a quadratic power of L_2-norm:

$$b_k = \|\nabla(s_k)\|_2^2 \tag{7}$$

Based on the formula of estimated bandwidth, the objective of the VMD can be expressed as:

$$\min_{\{w_k(t),\omega_k(t)\}} \sum_k b_k \quad \mathrm{s.t.} \sum_k w_k(t) = f(t) \tag{8}$$

where, $f(t)$ is the original signal.

Thereafter, the vibration signal was decomposed to obtain the chatter frequency band under a certain number of modals and used to separate the original time-domain information containing the main modal from its nearby frequency information, making the feature information more sensitive. After obtaining different chatter frequency bands and signal subsequences, the information entropy of sub-modal signals can be calculated as chatter features:

$$En_i = -\sum_{j=1}^{n} x_{ij}\log x_{ij} \tag{9}$$

where, En_i is the information entropy of the i^{th} signal subsequence x_i; n is sequence length.

Once the information entropy vector was obtained, the dimensionality reduction algorithm (e.g., SVD and PCA) was introduced to reduce the dimension of the obtained vector by removing the irrelevant components. Then, the sample vectors of standard cutting chatter parameters were used to train the SVM. The SVM is a reasonable technique to identify cutting chatter, because it finds the optimal classification hyperplane to maximize the sum of Euclidean distances of heterogeneous support vectors. In addition, the entropy of each signal subsequence obtained by VMD was imported to the SVM for classification, marking the completion of online cutting chatter identification. The workflow of the SVM-based online cutting chatter identification is illustrated in Fig. 6.

Fig. 7 shows the results of SVM-based online cutting chatter identification. It can be seen that the identification accuracy was as high as 92.57 %, after 60 iterations of training (in each iteration, the sample set was randomly divided into a test set and a training set).

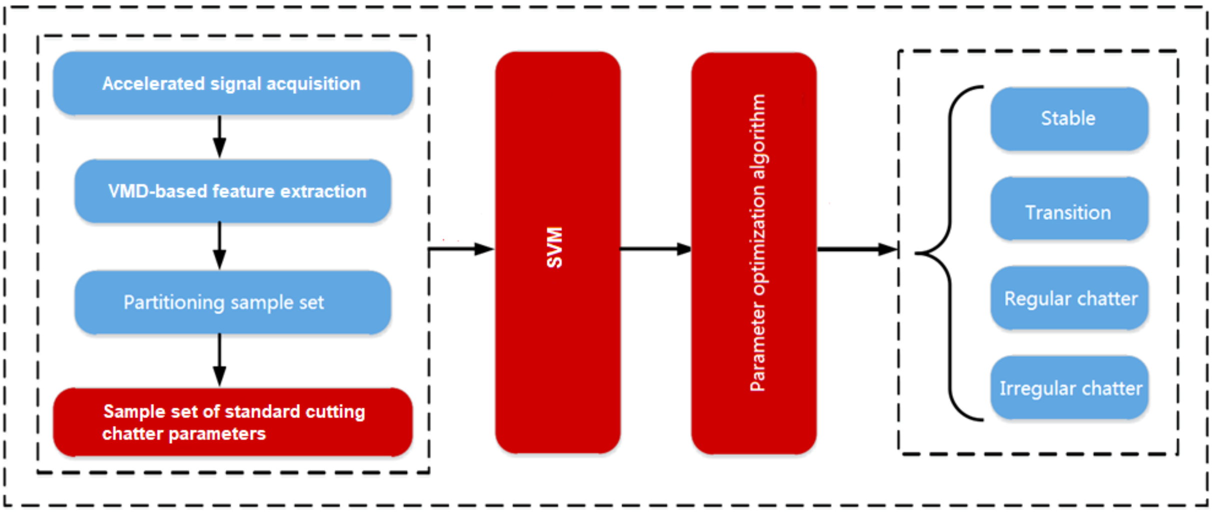


Figure 6: The workflow of the SVM-based online cutting chatter identification.

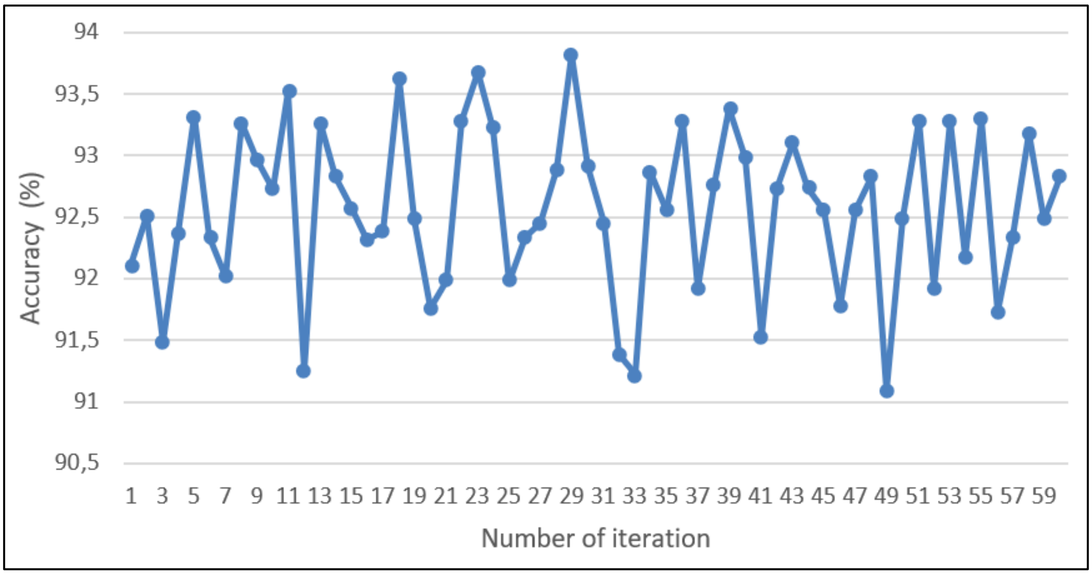


Figure 7: The results of the SVM-based online cutting chatter identification.

5. CONCLUSIONS

This paper mainly attempts to identify chatter state accurately in the cutting process. To this end, actual cutting experiments were carried out based on analytical modelling, and the vibration signal was collected and analysed to classify chatter states. On this basis, the vibration signal was transformed into wavelet time-frequency spectrum, which was then classified by a self-designed DR-CNN. Then, the effects of different parameter settings on the classification accuracy were analysed, and the optimal setting was applied to offline cutting chatter identification. Finally, an online identification method was designed for cutting chatter based on the SVM and parameter optimization. The proposed method greatly improves the accuracy of online identification of cutting chatter.

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