Chatter Detection in Milling Process Based on the Combination of Wavelet Packet Transform and PSO-SVM

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Chatter detection in milling Process based on the combination of wavelet packet transform and PSO-SVM

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Abstract

Chatter has become the mainly limiting factor in the development of rapid and stable machining of machine tools, which seriously impacts on surface quality and dimensional accuracy of the finished workpiece. In this paper, a novel method of chatter recognition was proposed based on the combination of wavelet packet transform (WPT) and PSO-SVM in milling. The collected vibration signal was pre-processed by wavelet packet transform (WPT), and the wavelet packets with rich chatter information were selected and reconstructed. The selected wavelet packets can reduce the redundant noise and useless information. a combination of 10 time-domain and 4 frequency-domain feature parameters were obtained through calculating the reconstructed vibration signals. Compared to three methods of k-fold cross validation (k-CV), genetic algorithm (GA) and particle swarm optimization (PSO) to optimize the input parameters of SVM, the experiment results were shown that the PSO algorithm has is characterized by high accuracy. The proposed approach can recognize the stable, chatter and transition states more accurately than the other traditional approaches.

Keywords

Chatter, Wavelet packet transform, Feature parameters, PSO-SVM, Chatter recognition

1. Introduction

Chatter is one of the biggest unfavorable factors in achieving high performance metal-cutting operations, which is a self-excited vibration happened between workpieces and cutting tools[1]. It occurs in any machine tooling process and can directly affect the surface quality and dimensional accuracy of the finished workpiece, seriously damaging the tool and reducing the life of the machine tools. Timely chatter is detected, which is a prerequisite for improving production efficiency and reducing manufacturing cost. However, the cutting process in the milling is non-stationary due to machine tool spindle wear, the change of operating temperature and workpiece stiffness, and other non-linear factors[2]. Therefore, with the cutting environment changing, the methods of chatter detection and recognition have always been significant important issues.

In the past few decades, many researchers paid attention to chatter detection, which has been a research hotspot. In order to detect the phenomenon of chatter, some sensors were generally applied to obtain chatter signal, such as acceleration sensor, acoustic emission, current sensor, microphone and so on [3-6]. No matter which sensor is chosen, it is significant to extract the chatter features and design the related chatter indicators for chatter detection. Ye et al. [7] calculated the standard deviation and the mean of root mean square sequence of the real-time acceleration signals, and selected the ratio of the standard deviation to the mean as the indicator to identify the occurrence of chatter. Tangjitsitcharoen [8] used the power spectrum density of dynamic cutting force signals to detect chatter state in turning process. In order to improve the robustness and reliability of chatter detection under variable cutting conditions, multi-sensor fusion is used for chatter detection. Kuljanic et al. [9]compared the sensibility of chatter onset of several sensors, and found that three or four sensors are the most promising solution for reliable and robust chatter identification. Pan et al. [10]studied the boring chatter identification with multi-sensors by multi-feature parameters and manifold learning, and found that multi-features extracted from different kinds of sensors can improve the recognition rate. However, some sensors are not applicable in practical application of cutting process. For example, to ensure the reliability of measurements, the acoustic emission need to be close to the tool-workpiece machining location [11]. And force sensor and displacement sensor might be costly and difficult for installation. In order to extract more chatter feathers, Wan et al. [12] extracted manually selected 8 features in time domain and frequency domain and 8 features automatically extracted by features extracted by stacked-denoising autoencoder, highly improving the accuracy and reliability of milling chatter identification based on Adaboost-SVM.

During the actual cutting process, the acquired signals contain a lot of noise. In order to extract the chatter-sensitive features, the method of signal processing is much more significant. The proper method for processing time-varying nonstationary signal, including short-time Fourier transform, Wigner–Ville distribution, wavelet transform, wavelet packet transform, Hilbert–Huang transform, etc. can effectively reduce the content of noise and enhance the Signal Noise Ratio (SNR). Fu et al. [13] used the empirical mode decomposition (EMD) to preprocess the vibration signal decomposing into a series of intrinsic mode functions (IMFs) to quantize the spectrum characteristic for online detection system. Ji et al. [14] adopted the ensemble empirical mode decomposition (EEMD) to decompose the acceleration signals, and the IMFs with the feature information of milling process were selected to the detect milling chatter timely. However, due to less theoretical background, the issue of mode mixing and end effects still remains [15]. Wavelet packet transform (WPT) is an effective signal processing method, which is especially used to deal with non-stationary signal. Compared short-time Fourier transform, WPT can overcome the shortcoming of short-time Fourier transform on a frequency-domain resolution. It can offer the low-pass band and high-pass band of signal at the same time, obtaining the high time-frequency resolution. Hence, in the process of milling, the measured signal was preprocessed by wavelet packet transform, which can effectively extract the frequency band with rich chatter information. Cao et al. [16] applied WPT as a preprocessor to denoise the measured signals, enhancing the performance of the Hilbert–Huang transform. They found that the mean value and standard deviation of the Hilbert–Huang spectrum can identify the chatter effectively. Yao et al. [17] used the standard deviation of wavelet transform and the wavelet packet energy ratio in the chatter-emerging frequency band as chatter vectors for the identification stable, transition and chatter state.

Although the extracted features in signals with preprocessing can present the degree of stability of the machining condition, threshold methods are usually applied to identify the machining state [18]. Therefore, additional efforts are required to implement intelligent monitoring systems of chatter detection. Through a learning process, the stable and unstable states in cutting process are discriminated. Several recognition techniques such as neural network, fuzzy logic, hidden Markov models (HMM) and support vector machine (SVM) have been utilized to detection variable machining conditions. Teti et al. [19] investigated that the neural network and fuzzy logic techniques are widely applied in cutting condition monitoring. Zhang et al. [20] proposed a hybrid approach of combining the advantages of artificial neural network (ANN) and hidden markov model (HMM) for monitoring cutting chatter, and found that the cu0tting chatter can be detected timely. Alternatively, SVM, as a small-sample learning machine, has many unique advantages in nonlinear and high-dimensional pattern recognition, which owns the greatest generalization ability and minimizes the classification error. SVM is widely used for chatter detection in milling process, as it has simple geometric interpretation and is suitable for small sample sizes [21-23]. However, penalty parameter C and kernel function parameter such as the gamma (γ) for the radial basis function (RBF) of SVM seriously impact on the recognition rate of SVM classifier. Hence, the parameter optimization of SVM is an ongoing research issue. In order to get the best of penalty parameter and kernel function parameter, several optimization algorithms are employed to SVM. Peng et al. [24] used the k-fold cross validation method (K-CV) to optimize the best C and gamma of RBF kernel function. But this approach is a local search strategy, which leads to that the SVM classifier are prone to falling into the local minimum[25, 26].

The genetic algorithm (GA) was used to optimize the SVM parameters to improve classification accuracy in wheel wear monitoring, which achieved a great performance[27]. The genetic support vector machine (GA-SVM) is used to drill wear state identification, the experimental results indicated that using GA-SVM can effectively track the trend of tool wear[28]. Subsequently, Particle swarm optimization (PSO) is used to optimize the SVM parameters, successfully applying to the bearing fault diagnosis[4, 29]. Even though genetic algorithm (GA) and particle swarm optimization(PSO) have good advantage of parameter optimization of SVM in terms of classification recognition, PSO is simple to operate and reduce the computation time significantly with respect to GA[30, 31]. Wang et al. [32] proposed a hybrid chatter detection method is for chatter classification in end milling, and found that this approach can recognize the stable, transition, and chatter states more accurately than the other traditional approaches by PSO optimizing the input parameters of SVM.

In this regard, this paper presents a study on chatter detection in monitoring system by the multi-feathers of time-frequency domain. Firstly, the measured vibration signal is preprocessed by wavelet packet transform (WPT), and two wavelet packets with rich chatter information were selected and reconstructed. Then, 10 time-domain and 4 frequency-domain feature parameters of the reconstructed vibration signal are calculated as feature vectors of chatter identification, which consists of the original feature set. Finally, through comparison of k-fold cross validation, genetic algorithm (GA) and particle swarm optimization (PSO) optimizing the SVM parameters, the PSO-SVM could improve obviously the accuracy of chatter recognition than the others.

2. Proposed methodology of Chatter detection

The scheme of the proposed chatter detection method is shown in Fig. 1. WPT was used to decompose and reconstruct the collected vibration signals, and the energy ratio was chosen as selecting characteristic wavelet packet with the rich information in the chatter-emerging frequency band. Then 10 time-domain and 4 frequency-domain features were selected as recognition parameters of chatter by calculating the reconstructed vibration signal, which formed feature vectors. Finally, the SVM-PSO model was used for feature classification to obtain the final recognition results.

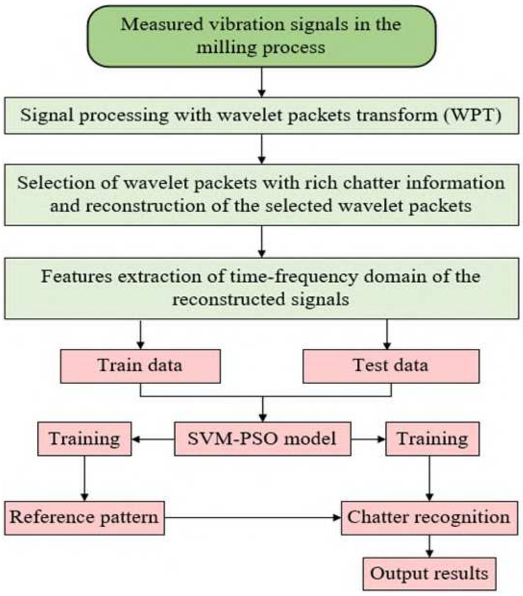

Fig. 1 Flowchart of the chatter detection system

2.1 Feature extraction of chatter

When chatter occurs during the machining process, the amplitude and distribution of time-domain signal may be different from that of time-domain signal of stable machining. Therefore, we supposed that $x_i\,(i = 1, 2, \ldots, N)$ was a signal series, N was the number of collected data points. We chose 10 time-domain features for identifying chatter state, as shown in Table 1. From Table 1, x_m 、x_p and x_{rms} represented the amplitude and energy of time-domain signal respectively. x_{std} 、x_{ske} 、x_{kur} 、CF 、CLF 、SF and IF reflected the time series distribution of time-domain signal.

Table 1 Time-domain feature parameters

Feature	Equation	Feature	Equation
Mean:	$x_m = \frac{1}{n}\sum_{i=1}^{n} x_i$	Kurtosis:	$x_{kur} = \frac{\sum_{i=1}^{n}(x_i - x_m)^4}{(n-1)x_{std}^4}$
Standard deviation:	$x_{std} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - x_m)^2}$	Crest factor:	$CF = \frac{x_p}{x_{rms}}$
Root mean square: x_{rms}	$x_{rms} = \sqrt{\frac{1}{n}\sum_{i-1}^{n}(x_i)^2}$	Clearance factor:	$CLF = \frac{x_p}{\left(\sqrt{\frac{1}{n}\sum_{i=1}^{n}\lvert x_i\rvert}\right)^2}$
Peak:	$x_p = \max(\lvert x_i\rvert)$	Shape factor:	$SF = \frac{x_{rms}}{\frac{1}{n}\sum_{i=1}^{n}\lvert x_i\rvert}$
Skewness:	$x_{ske} = \frac{\sum_{i=1}^{n}(x_i - x_m)^3}{(n-1)x_{std}^3}$	Impulse factor:	$IF = \frac{x_p}{\frac{1}{n}\sum_{i=1}^{n}\lvert x_i\rvert}$

In addition, considering that some hidden chatter information cannot reflect directly in time-domain scale. Because the amplitude and distribution of frequency components of time-domain signal may change with the occurrence of chatter when chatter occurs [13]. In this regard, we selected 4 frequency-domain parameters as feature recognition of chatter, as described in the following.

(1) Mean square frequency: $MSF = \dfrac{\sum_{j=1}^{m} f_j^2 S(f_j)}{\sum_{j=1}^{m} S(f_j)}$

(2) One-step autocorrelation function: $\rho = \dfrac{\sum_{j=1}^{n} \cos(2\pi f_j \Delta t) S(f_j)}{\sum_{j=1}^{n} S(f_j)}$

(3) Frequency centre: $FC = \dfrac{\sum_{j=1}^{n} f_j S(f_j)}{\sum_{j=1}^{n} S(f_j)}$

(4) Standard frequency: $FV = \dfrac{\sum_{j=1}^{m} \left(f_j - FC\right)^2 S(f_j)}{\sum_{j=1}^{m} S(f_j)}$

$f_j (j = 1, 2, \cdots, m)$ was the *j*-th frequency of power spectrum. And $S(f_j)$ represented the amplitude of power spectrum calculated by FFT. The *MSF* represented the energy of the vibration signal in the frequency domain. ρ and *FC* reflected the position change of the main band of signal. *FV* described the energy dispersion and concentration of signal in the frequency domain.

However, it takes a lot of time to calculate these four frequency-domain feature parameters by Fast Fourier Transform (FFT). To solve this issue, a fast calculation criterion of frequency-domain feature parameters was employed [29], the 4 frequency-domain feature parameters can be rewritten as shown in Table 2. Hence, in this paper, 10 time-domain and 4 frequency-domain features were selected as recognition parameters of chatter [33, 34], which formed feature vectors.

Table 2 Frequency-domain feature parameters

Feature	Equation
Mean square frequency:	$MSF = \dfrac{\sum_{i=2}^{n} \dot{x}^2}{4\pi^2 \sum_{i=1}^{n} x_i^2}$
One-step autocorrelation function:	$\rho = \dfrac{\sum_{i=2}^{n} x_i x_{i-1}}{\sum_{i=1}^{n} x_i^2}$
Frequency centre:	$FC = \dfrac{\sum_{i=2}^{n} x_i \dot{x}}{4\pi^2 \sum_{i=1}^{n} x_i^2}$
Standard frequency:	$FV = MSF - 4\pi^2 FC^2$

2.2 Wavelet packet transform

However, the measured vibration signal generally contains noise which is the disadvantage of identifying chatter both in the time and frequency domain. Therefore, it is very critical to suppress or eliminate the noise for the feature extraction of chatter. Since the noise is broadband, the measured signal is decomposed into some narrow band components, and the energy of noise will be dispersed in these narrow bands. Wavelet packet transform (WPT) is the best option available to solve this issue [16]. WPT is implemented by a basic two-channel filter bank, which is iterated over either the low-pass or high-pass branch. Therefore, it can not only decompose the low frequencies and the high frequencies, but also improve the time-frequency domain resolution. When the vibration signal is preprocessed by WPT before feature extraction, the chatter signal may be distributed in a specific frequency band, and the signal-to-noise ratio could be enhanced.

The wavelet method decomposes a time signal into a time-frequency scale according to the shifted and scaled signal decomposition of a prototype function which is called mother wavelet. Supposing that $\Psi(t) \in L^2$ is a function called mother wavelet, and $\Psi_{s,u}(t)$ with $s,u \in r$, and $s > 0$ are a family of shifted and scaled functions of a mother wavelet. An entire family of elementary functions by dilatations or contractions is produced by a modulated window $\Psi(t)$, and translations in time defined by Eq. (1) [35, 36]:

$$\Psi_{u,s}(t) = \frac{1}{\sqrt{s}} \Psi(\frac{t-u}{s}) \tag{1}$$

Where s and u are the scaling parameter and the position parameter.

In case of continues time of a function x(t), the wavelet transform (WT) is called a continuous wavelet transform (CWT), which is calculated by the inner product of the analyzed signal with a family of shifted and scaled wavelets, using the expression Eq. (2) [35, 36]:

$$CWTx(s,u) = \left\langle x(t), \Psi_{u,s}(t) \right\rangle = \frac{1}{\sqrt{s}} \int_{-\infty}^{+\infty} x(t) \Psi^{*}(\frac{t-u}{s}) dt \tag{2}$$

The advantage of CWT is very useful for the analysis of non-stationary signals, enabling the temporal location of the components in the frequency domain. However, the low analytical computational efficiency limits its off-line applications. For applications of processing real-time signal, wavelet packet transform (WPT) can decompose the signal into a mutually orthogonal set of wavelets, which is derived from the application of a pyramidal algorithm of convolutions with quadrature mirror filters, according to the coefficients presented in Eq. (3) and (4).

$$A_{j,k} = \sum_{l} g_{l-2k} A_{j-1,l} \tag{3}$$

$$D_{j,k} = \sum_{l} h_{l-2k} A_{j-1,l} \tag{4}$$

Where $A_{j,k}$ is scaling and $D_{j,k}$ is wavelet coefficient, j is the number of transformation levels with j =1, 2, …; k is the number of scaled and wavelet coefficients with k = 1, 2, …, $N \times 2^j$, where N is the total number of samples of the original signal, h and g are low-pass and high-pass coefficients of the scaled function and wavelet function respectively, and l is the filter length. These coefficients successively decompose the original signal into approximation (low frequency) or detail (high frequency) signals using the scaled and wavelet coefficients respectively.

Supposing there is a vibration signal x(t), which is decomposed by the WPT. Then the decomposed frequency-band signal $x_{i,j}$(t) is generated, where $x_{i,j}$(t) represents the j-th frequency-band signal at level i, and where j=1,2,...,J, and J=2^I , which is the number of decomposed frequency-band signals, and i=1,2,…,I, where I is the number of decomposition levels. As an illustration, a three-level WPT decomposition process of x(t) is described in Fig. 2.

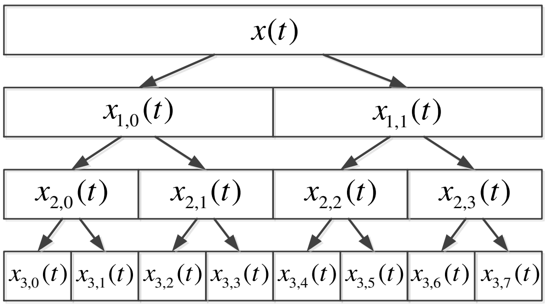

Fig. 2 A three-level WPT decomposition process

The frequency bands of the decomposed wavelet packets which include abundant chatter information need to be identified accurately before chatter feature is extracted. To find out this best frequency band, the energy ratio can represent cutting conditions in the milling. In stable milling process, energy of wavelet packet node focuses on the multiple frequency bands. When chatter occurs, energy ratio of wavelet packet node including chatter frequencies will dramatically increase. So the biggest energy ratio of wavelet packet with rich information can be selected as the characteristic wavelet packets and reconstructed. Then the chatter features are available by calculating the reconstructed wavelet packets.

2.3 Chatter recognition based on PSO-SVM

2.3.1 The theory of SVM

Support vector machine (SVM) is derived from statical learning theory, which is proposed according to optimal hyperplane in the case of linear separable. SVM is extensively applied to regression and classification. This section briefly introduces the application of SVM classification[37, 38].

Considering a set of sample data which is denoted as $\left\{(\boldsymbol{x}_i, y_i), i=1,2,\cdots,n\right\}$, where $\boldsymbol{x}_i$ are the input vectors, and $y_i \in \{-1,1\}$ are the class label of $\boldsymbol{x}_i$. The task of SVM is to find out an optimal hyperplane which can separate two datasets with the maximal margin. With using the nonlinear function φ, the input vectors $\boldsymbol{x}_i$ are mapped into a high dimensional feature space $\boldsymbol{F}$. Then, the maximum margin separating hyperplane in $\boldsymbol{F}$ is produced, which is denoted as:

$$\boldsymbol{\omega}\cdot\varphi(\boldsymbol{x}_i)+b=0 \tag{5}$$

Where $\boldsymbol{\omega}$ is the weight vector and b is the bias term. $\boldsymbol{\omega}$ and b determine the position of the separating hyperplane. The optimal hyperplane is found out by solving the following constrained optimization problem:

$$\text{Minimize: } L(\boldsymbol{\omega}, b, \xi) = \frac{1}{2}\|\boldsymbol{\omega}\|^2 + C\sum_{i=1}^{N}\xi_i$$

$$\text{Subject to: } y_i\left(\boldsymbol{\omega}\cdot\varphi(\boldsymbol{x}_i)+b\right)-1+\xi_i \geq 0,\ i=1,2,\cdots,n \tag{6}$$

Where C is the penalty parameter which represents a trade-off between training error and the margin, ξ_i are slack variables, and $\xi_i > 0$.

Using the Lagrange function, the problem can be rewritten as follows:

$$\text{Min} \quad L=\sum_{i=1}^{n}\alpha_i-\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i\alpha_j y_i y_j K\left(\boldsymbol{x}_i,\boldsymbol{x}_j\right)$$

$$\text{Subject to:} \ \sum_{i=1}^{n} y_i\alpha_i=0, 0\le\alpha_i\le C, \quad i=1,2,\cdots,n \tag{7}$$

Where α_i are the constants which called Lagrange multipliers and are determined in the optimization process. $K\left(\boldsymbol{x}_i,\boldsymbol{x}_j\right)$ is a symmetric and positive kernel function which denotes as $K\left(\boldsymbol{x}_i,\boldsymbol{x}_j\right)=\left\langle\varphi\left(\boldsymbol{x}_i\right)\cdot\varphi\left(\boldsymbol{x}_j\right)\right\rangle$, satisfying Mercer's theory. The derived training algorithm is guaranteed for minimization.

When the above optimization problem is solved, the weight vector $\boldsymbol{\omega}$ could be calculated by

$$\boldsymbol{\omega}=\sum_{i=1}^{n}\alpha_i y_i\varphi\left(\boldsymbol{x}_i\right) \tag{8}$$

Then, the non-linear decision function of SVM is described as following:

$$f\left(\boldsymbol{x}\right)=sign\left(\left[\boldsymbol{\omega}\cdot\varphi(\boldsymbol{x})\right]+b\right)=sign\left(\sum_{i=1}^{n}\alpha_i y_i K\left(\boldsymbol{x}_i,\boldsymbol{x}_j\right)+b\right) \tag{9}$$

2.3.2 Parameters selection of SVM with PSO

In the study, the selection of the parameters has a great influence on the performance of SVM. Like genetic algorithms (GA), PSO is a population-based search algorithm. However, unlike GA, PSO has no crossover and variation. In PSO, particles in the solution space following the optimal particle search. The advantage of PSO is simple and easy to achieve without many parameters need to be adjusted. Therefore, PSO algorithm is used to realize the parameters' selection of SVM.

Particle swarm optimization (PSO) was proposed by Kennedy and Eberhart in 1995, which is a kind of global search algorithm. It is inspired by complicated group behavior such as birds foraging. When birds are foraging, they can search for a simplest but effective way which is to search the zone around birds. Like evolutionary algorithms, PSO performs searches using a population (called swarm) of individuals (called particles) that are updated from iteration to iteration.

Assume there is an n-dimensional search space, the velocity and position of the *i*-th particle are $V_i=\left[v_{i,1}\ v_{i,2}\ \cdots\ v_{i,j}\right]$ and $X_i=\left[x_{i,1}\ x_{i,2}\ \cdots\ x_{i,j}\right]$, respectively. Where $i=1,2,\cdots,m$, *m* represents the scale of particles in swarm, and $j=1,2,\cdots,d$. According to the PSO algorithm, each particle moves in the direction of its best previous position and the global best position is discovered by any particles in the swarm. By evaluating fitness of each particle, the best position (called *pbest*) of the *i*-th particle is calculated, and then the optimal position (*gbest*) of all particle group is found. Each particle calculates its own velocity and updates its position in each iteration, and the global best value is ultimately obtained. Let *k* denote the current generation. To search for the optimal solution, the current velocity and position of the *d*-th dimension of the *i*-th particle at time *k* is described as follows[29]:

$$v_{i,j}(k+1)=\omega v_{i,j}(k)+c_1r_1[p_{i,j}-x_{i,j}(k)]+c_2r_2[p_{g,j}-x_{i,j}(k)] \tag{10}$$

$$x_{i,j}(k+1)=x_{i,j}(k)+v_{i,j}(k+1) \quad i=1,2,\cdots,m \ \ j=1,2,\cdots,d \tag{11}$$

In the above formula, c_1 and c_2 denote as accelerating constants, and $c_1, c_2 > 0$. r_1 and r_2 are random numbers in the range of [0,1]. $p_{i,j}$ represents the best position of *i*-th particle in j-dimensional search space, and $p_{g,j}$ the best position of the whole swarm. $v_{i,j}$ represents the current velocity of *i*-th particle in j-dimensional search space, $v_{i,j} \in [-V_{\max}, V_{\max}]$, and $V_{\max}$ represents the maximum limited velocity. ω is an inertial weight which is utilized to balance the capabilities of local exploration and global exploration. A popularly used inertial weight is linearly decreasing weights (LDW)[30], which is defined as

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{k_{\max}} k \tag{12}$$

Where $\omega_{\max}$ is the maximal inertia weight, $\omega_{\min}$ is the minimal inertia weight, *k* is iterative number of controlling procedure process, $k_{\max}$ is the maximal iteration of PSO.

In this study, the radial basis function (RBF) is selected as the kernel function, and the parameter of RBF is the gamma (γ). Therefore, the classification performance of SVM is influenced by the two user-determined parameters, which are penalty parameter C and the kernel function parameter γ.

In PSO, the particle is composed of the parameters C and γ. The procedure of optimizing the SVM parameters with PSO is presented in Fig. 3, which is displayed as follows:

(1) Input data. Training and testing sets are represented.

(2) Particle swarm initialization. Set the accelerating constant c_1 and c_2. Define the maximum number of iterations $k_{\max}$, and set the current number of iterations $k = 1$. Randomly generating *m* particles in the d-dimensional space, the velocity and position of *i*-th particle are denoted as $V_i = \left[v_{i,1} \ v_{i,2} \ \cdots \ v_{i,d} \right]$ and $X_i = \left[x_{i,1} \ x_{i,2} \ \cdots \ x_{i,d} \right]$, respectively;

(3) Evaluate the fitness of all particles. For each particle, calculate the value of the optimization function for each particle in corresponding search space respectively;

(4) Comparing the current fitness of each particle with its own historical best position *pbest*. If *pbest* is smaller than the current fitness of particle, then *pbest* is replaced with the current fitness and become the current position. Otherwise, *pbest* remains the same.

(5) Comparing the current position of all particles with their own historical best position g*best* of the whole swarm. If *gbest* is smaller than the current position of particle, then *gbest* is replaced with the current position of the whole swarm and become the current position of all particles. Otherwise, *gbest* remains the same.

(6) Update velocity and position of particles. Update the positions and velocities of all particles according to the equations of the position and velocity as in Eq. (10) and (11); then form new particle swarms, go to step 3.

(7) Judging whether the stopping criterion is satisfied, if "Yes" then ending the iteration operation; if

“No” then going to Step (3). The stopping criterion could be a maximal iteration, or that the fitness of the particles is smaller than a given required precision.

(8) Obtain optimized SVM parameters C and γ.

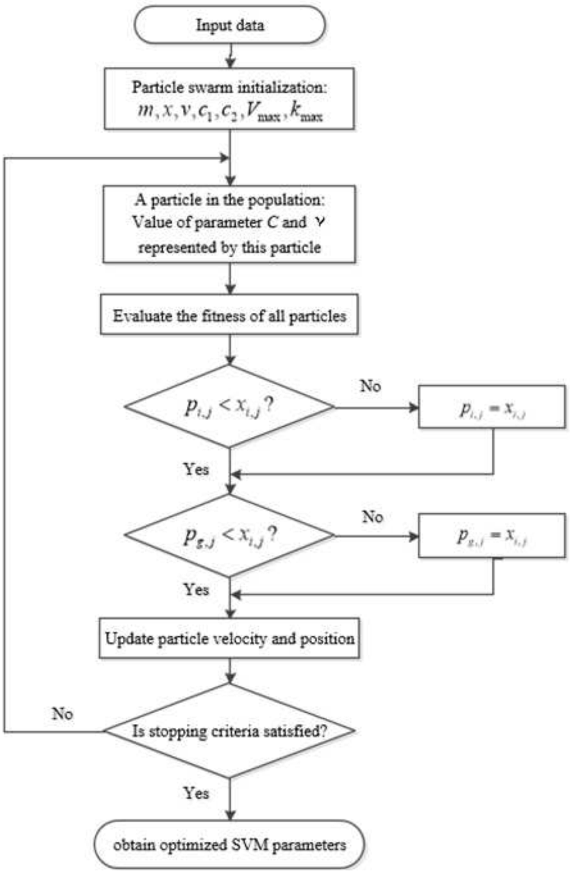

Fig. 3 The procedure of optimizing the SVM parameters with PSO

3. Experimental setup of end milling

To demonstrate the effectiveness of the proposed approach of chatter recognition, we conducted the cutting experiments of aluminum 6061 on three-axis milling machine center of VMC1165B, as shown in Fig. 4. The tool is a carbide end mill cutter with two flutes, and besides the cutting tool’s diameter and overhang are 8mm and 44mm respectively. An acceleration sensor is mounted on the spindle housing and a data acquisition card of NI USB-6341 is used to acquire the acceleration signals during milling. The sampling frequency of signals is set to 12000 Hz. In addition, the whole milling process is under the dry condition.

Fig. 4 Experimental setup

It is well known that the chatter is closely related to the depth of cut, spindle speed, feed rate[39]. For the validation of the proposed method in this study, when we fixed the spindle speed, the cutting depth started from 0.2mm and increased 0.2mm each experiment until chatter occurred. The other cutting parameters in this experiment are shown in Table 3.

Table 3 Cutting conditions

Workpiece	AL6061
Tool	Carbide End Mills Φ8 mm
Spindle speed(rpm)	3000,4000,5000,6000,7000
Feed per tooth(mm/z)	0.02

In addition, to obtain the modal of milling-workpiece system, hammer test is done before the milling experiment. During the hammer test, the method of single-point impaction and single-point respond is applied to obtain the machine tool's transfer function. The hammer hits the location which is on the tool tip. By calculating a third orders natural frequencies are 1494, 2041, and 4160 Hz.

4. Results and discussion

4.1 The collected vibration signal analysis of milling processes

Fig. 5 (a) and (b) are shown the three typical processing states of vibration signal (e.g., stable state, transition state, chatter state). Fig. 5 (c) and (f) are the partial enlarged vibration signals and FFT of stable cutting state in Fig. 5(a) respectively. Fig. 5 (d) and (h), (e) and (i) are the partial enlarged vibration signals and FFT of transition and chatter cutting state in Fig. 5 (b) respectively. From Fig. 5 (c) and (f) in the stable cutting state, it is seen that the amplitude is small, and the distribution of frequency components is dispersal, the main frequency peaks mainly concentrating on the 1301 Hz, 2039 Hz, 2801 Hz, 4078 Hz, 5145 Hz. These frequency components nearly correspond with first natural frequency, second order natural frequency, twice first natural frequency, third order natural frequency and fourfold first natural frequency of the system. When increasing spindle speed up to 6000 r/min and axial depth of cut up to 0.8mm, the slight chatter appears, which is called transition state of chatter. In the transition state, the amplitude of vibration signals increases slightly, but the distribution of the frequency components has been changed drastically (see Fig. 5(h)). Consequently, other frequency components are suppressed, and the frequency focuses on the around 2824Hz, which is close to the twice first natural frequency of the system [40]. This is contribute to that the helix angle of milling tool may have an significantly important role on instability due to repetitive impact driven chatter [41]. In addition, the occurrence of chatter inhibits the production of other frequencies. Subsequently, the severe chatter occurs with the cumulative effect of energy, as shown in Fig. 5(b). The amplitude of vibration signals becomes larger, and the chatter frequency of 2824Hz is further enhanced.

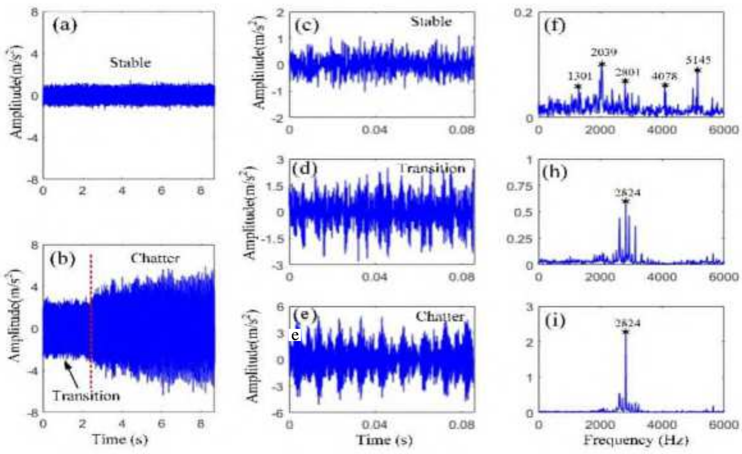

Fig. 5 The measured vibration signals in three states and their FFT.

Fig. 5 (a) The stable cutting state of vibration signals under cutting conditions of spindle speed 5000 r/min, axial depth of cut 0.2mm, and feed rate 0.2 mm/z. (b) The transition and chatter cutting states of vibration signals under cutting conditions of spindle speed 6000 r/min, axial depth of cut 0.8mm, and feed rate 0.2 mm/z. (c) and (f) were the partial enlarged vibration signals and FFT of stable cutting state in (a) respectively. (d) and (h), (e) and (i) were the partial enlarged vibration signals and FFT of transition and chatter cutting state in (b) respectively.

The purpose of chatter detection is to effectively identify the infantile chatter state to avoid the unfavorable effect on the workpiece and the tools. Therefore, the effective and accurate recognition of transition stage of chatter is significant important. In this regard, this paper emphasized on investigating the feature extraction of the transition stage of chatter. In this paper, the db10 is chosen as the wavelet basis function which has the better orthogonality. The measured vibration signal is decomposed four levels by WPT in terms of stable and chatter state in end milling process. The 16 wavelet packets are obtained correspondingly. Fig. 6 is the description of the four-level WPT of reconstructed signal in the chatter transition state and the corresponding FFT in each frequency band. It can be shown that the amplitude of the acceleration signal in the frequency bands $x_{4,7}$ (2625 – 3000 Hz) and $x_{4,8}$ (3000 – 3375 Hz) is larger than the signal in other frequency bands. So, the chatter frequency can be determined in the frequency bands $x_{4,7}$ and $x_{4,8}$. According to the amplitude spectrum of the acceleration signal, the energy ratio was calculated, as shown in Table 4. We also find that when chatter taking place, the energy is mainly concentrated in the wavelet packets of $x_{4,7}$ and $x_{4,8}$, where the vibration energy was concentrated around the chatter frequency and the energy and amplitude would increase sharply. Therefore, the wavelet packets of $x_{4,7}$ and $x_{4,8}$ with rich chatter information are selected as the characteristic wavelet packets and reconstructed. The reconstructed vibration signal of characteristic wavelet packets and corresponding to FFT are shown in Fig. 7. From the picture, after screening the characteristic wavelet packets, it is found that redundant noise and useless information is effectively removed, the time-domain features of reconstructed vibration signal become more obvious, and the frequency spectrum retains a complete characteristic information of transition state of chatter. Therefore, the vibration signal with preprocessing by WPT has an important effect on the extraction of feature vectors and the noise reduction of signal. Then, according to the analysis of section 2.1, we calculate 10 time-domain and 4 frequency-domain feature parameters for each collected sample respectively. These feature parameters are selected as feature vector to identify cutting state in the milling process. Fig. 6 The reconstructed vibration signal of each frequency band and their amplitude spectrum in the transition state of chatter corresponding to Fig. 5 (d).

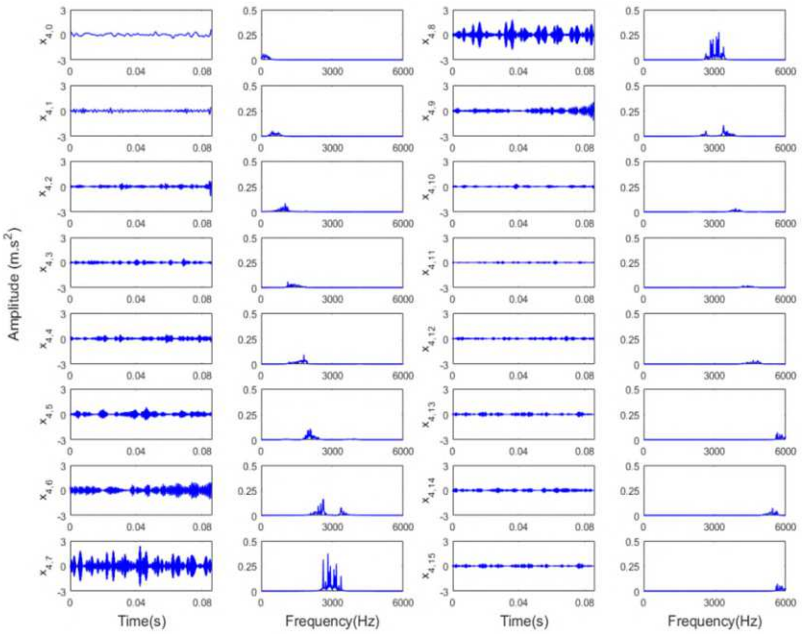

Fig. 6 four-level WPT of reconstructed signal in the chatter transition state and their corresponding FFT

Table 4 Energy ratio in the frequency bands of wavelet packet

Energy ratio in wavelet packet node	Cutting state		
	Stable state	Transition state	Chatter state
$x_{4,0}$ (0 – 375 Hz)	0.0537	0.0809	0.0127
$x_{4,1}$ (375 – 750 Hz)	0.0568	0.0168	0.0055
$x_{4,2}$ (750 – 1125 Hz)	0.0522	0.0588	0.0055
$x_{4,3}$ (1125 – 1500 Hz)	0.0738	0.0146	0.0049
$x_{4,4}$ (1500 – 1875 Hz)	0.0789	0.0246	0.0069
$x_{4,5}$ (1875 – 2250 Hz)	0.2125	0.0398	0.0132
$x_{4,6}$ (2250 – 2625 Hz)	0.0648	0.1036	0.0577
$x_{4,7}$ (2625 – 3000 Hz)	0.0581	0.3301	0.5617
$x_{4,8}$ (3000 – 3375 Hz)	0.0556	0.1999	0.2850
$x_{4,9}$ (3375 – 3750 Hz)	0.0672	0.0619	0.0167
$x_{4,10}$ (3750 – 4125 Hz)	0.0468	0.0106	0.0059
$x_{4,11}$ (4125 – 4500Hz)	0.0270	0.0036	0.0032
$x_{4,12}$ (4500 – 4875 Hz)	0.0175	0.0095	0.0045
$x_{4,13}$ (4875 – 5250 Hz)	0.0748	0.0104	0.0037
$x_{4,14}$ (5250 – 5625 Hz)	0.0254	0.0173	0.0067
$x_{4,15}$ (5625 – 6000 Hz)	0.0350	0.0176	0.0063

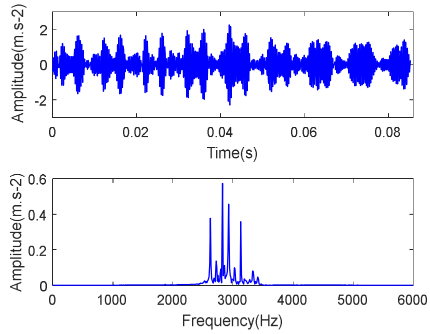

Fig. 7 The reconstructed vibration signal and FFT of characteristic wavelet packets of $x_{4,7}$ and $x_{4,8}$ in the transition state

4.2 Chatter identification based on time-frequency characteristics of WPT and PSO-SVM

This paper mainly focused on the infantile chatter identification based on the vibration signal, where is in the transition state shown in Fig. 5(b). The vibration signals in stable and transition state are collected under the cutting conditions, as shown in Table 1. Then 60 samples are obtained, where 30 samples are in cutting stable state and the others are in chatter transition state. Each sample has 1024 data points, which are processed with WPT and calculated to extract 14 time-frequency feature parameters as feature vector of chatter. Randomly 20 samples are selected as training data from stable samples and transition samples respectively. The remaining samples are selected as testing data.

According to the previous analysis in this paper, inappropriate penalty parameter C and kernel function parameter γ may cause the over-fitting and under-fitting of SVM classifier, which has important influence on the prediction accuracy of classification. But in the process of practical application, the optimal value of C and γ is not easy to determine. Therefore, the SVM parameters should be set in advance before the application of SVM. In this study, The PSO algorithm is used to select and optimize the penalty parameter C and kernel function parameter γ of SVM classifier. The initialized parameter values of PSO-SVM are set as follows. The swarm size is set to 20 particles, and the maximum number of iterations is 200. The accelerating constant c_1 and c_2 are set to 1.5 and 1.7 respectively. The searching range of parameter C of SVM is between 0.1 and 100, while the searching range of parameter γ of SVM is between 0.01 and 1,000. The fitness curves of the evolutionary algebra of PSO are shown in Fig. 8. The chatter identification accuracy rate of training data are all 95%, and the prediction accuracy rate is 95%, as shown in Table 5. At this point, the parameter values of SVM are C= 74.89 and γ=0.01.

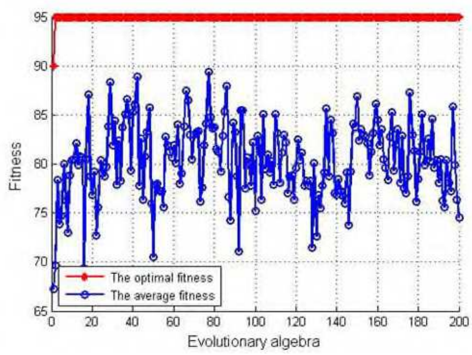

Fig. 8 The adaptive evolutionary curves of PSO

In addition, in order to demonstrate the effectiveness of the developed PSO-SVM approach in chatter detection, the three other methods of standard support vector machine (SVM), k-fold cross validation support vector machine (k-CV-SVM) and genetic algorithm support vector machine (GA-SVM) were selected and compared for chatter identification. The standard SVM parameters are set to C=2 and γ=1, which is as a reference. And the initialized parameter values of k-CV-SVM are set 3-fold Cross Validation, $2^{-8} \le C \le 2^{8}$ and $2^{-8} \le \gamma \le 2^{8}$. The initialized parameter values of GA-SVM are set as follows. The maximum evolutionary algebra and maximum population are 200 and 20 respectively. And the crossover probability and mutation probability are 0.4 and 0.01 respectively. The searching range of parameter *C* and γ of SVM is the same as PSO. The classification accuracy of k-CV method is shown as Fig. 9, and the fitness curves of the evolutionary algebra of GA are shown as Fig. 10. The accuracy of each method is shown as Table 5. From Table 5, it is indicated that chatter identification accuracy rate of training data are all 95% under the same conditions, while the prediction accuracy rate of testing data is significantly different. The prediction accuracy rate is 90% with standard support vector machine (SVM), and the prediction accuracy rate is only 85% using the optimized SVM parameters with k-CV as well as the optimized SVM parameters with GA, but the prediction accuracy rate is 95% with the optimized SVM parameters with PSO. Thus, The PSO algorithm should be used to optimize the parameters (*C*, γ) of SVM.

Table 5. Chatter identification accuracy based on PSO-SVM

	Number of features	*C*	γ	Accuracy /%	
				Training set	Testing set
WPT+SVM	14	2	1	95	90
WPT+k-CV-SVM	14	0.758	1.32	95	85
WPT+GA-SVM	14	3.94	0.40	95	85
WPT+PSO-SVM	14	74.89	0.01	95	95

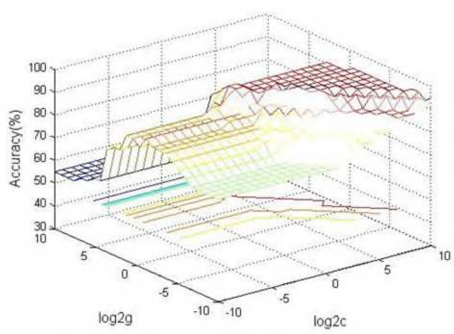

Fig. 9 The classification accuracy of k-CV method

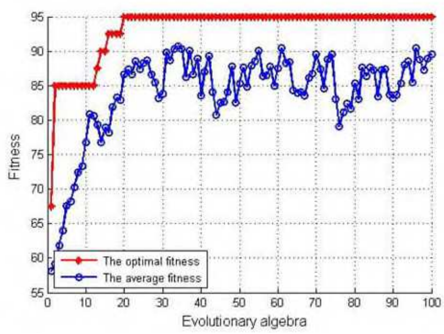

Fig. 10 The adaptive evolutionary curves of GA

5. Conclusion

This paper proposed a novel method of chatter recognition based on the combination of WPT and PSO-SVM in milling. The chatter detection is essentially a problem of pattern recognition, of which an important step is feature extraction. Before feature extraction, this study emphasizes on the in-depth analysis of the chatter-emerging frequency band of vibration signals with WPT. Chatter-emerging frequency bands are selected as characteristic wavelet packets and will be reconstructed. It is found that redundant noise and useless information is effectively removed to improve the accuracy of chatter diagnosis, the reconstructed vibration signals can completely express the amplitude and frequency of vibration when chatter occurs. Subsequently, a combination of 10 time-domain and 4 frequency-domain feature parameters are obtained through calculating the reconstructed vibration signals. Through extracting these features with rich information, the original chatter feature set is generated. Compared to three methods of k-fold cross validation (k-CV), genetic algorithm (GA) and particle swarm optimization (PSO) to optimize the input parameters of SVM, the experiment results are shown that the PSO algorithm has is characterized by high accuracy. The proposed approach can recognize the stable, chatter transition states more accurately than the other traditional approaches. In this regard, chatter suppression will be researched in future. By adjusting the spindle speed and the depth of cutting, the chatter may be suppressed based on the effect of milling parameters.

Author's contribution Qingzhen Zheng: methodology, software, writing (original draft preparation), experiment, and data processing; Guangsheng Chen: conceptualization, methodology, writing (review & editing), supervision, project administration; Anling Jiao: format checking, modification of figures and text.

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Availability of data Data will be available upon reasonable request.

Declarations

Ethical approval	Not applicable.
Consent to participate	Not applicable.
Consent to publish	All co-authors consent to the publication of this work.
Competing interests	The authors declare no competing interests.

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Figures

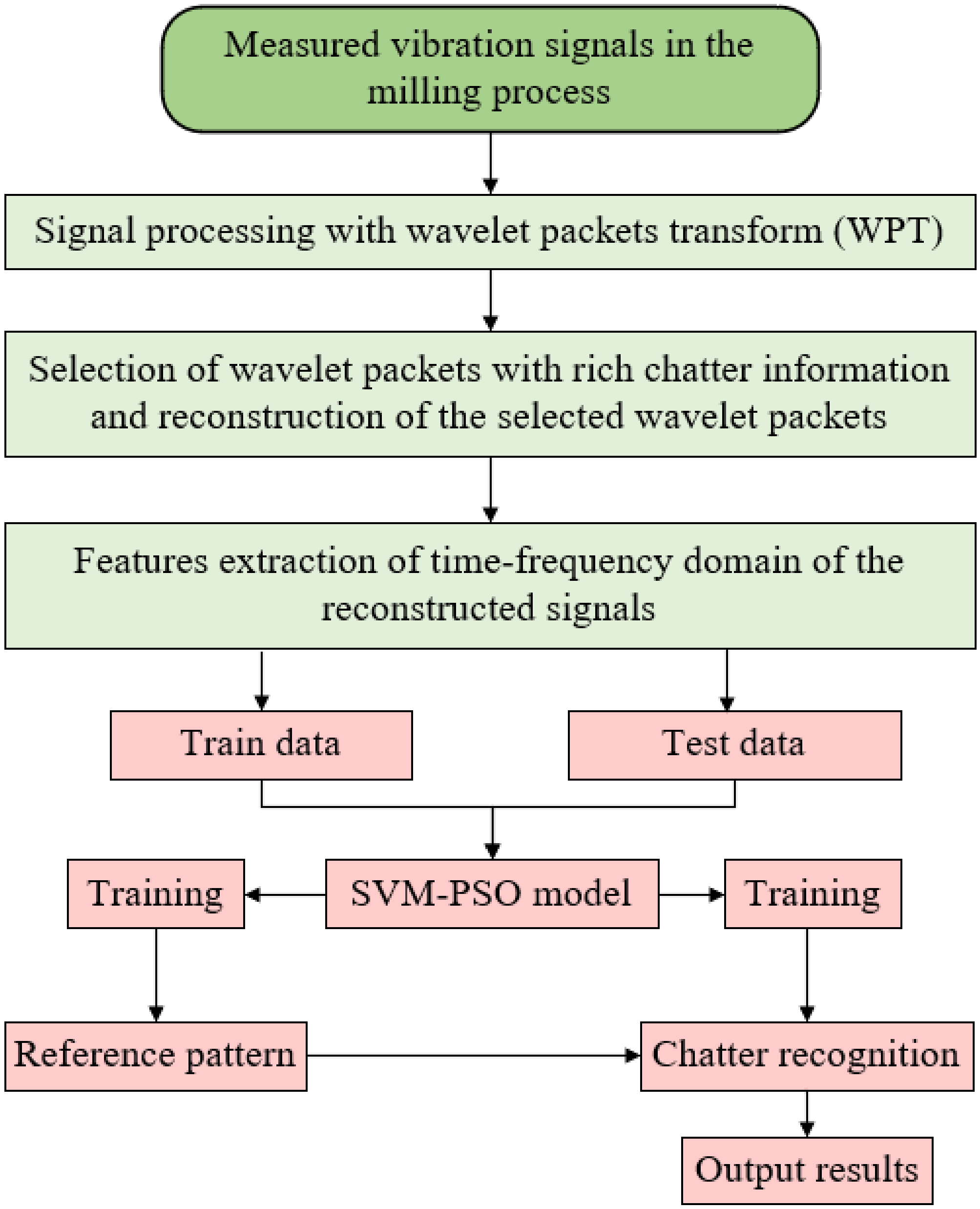

Figure 1

Flowchart of the chatter detection system

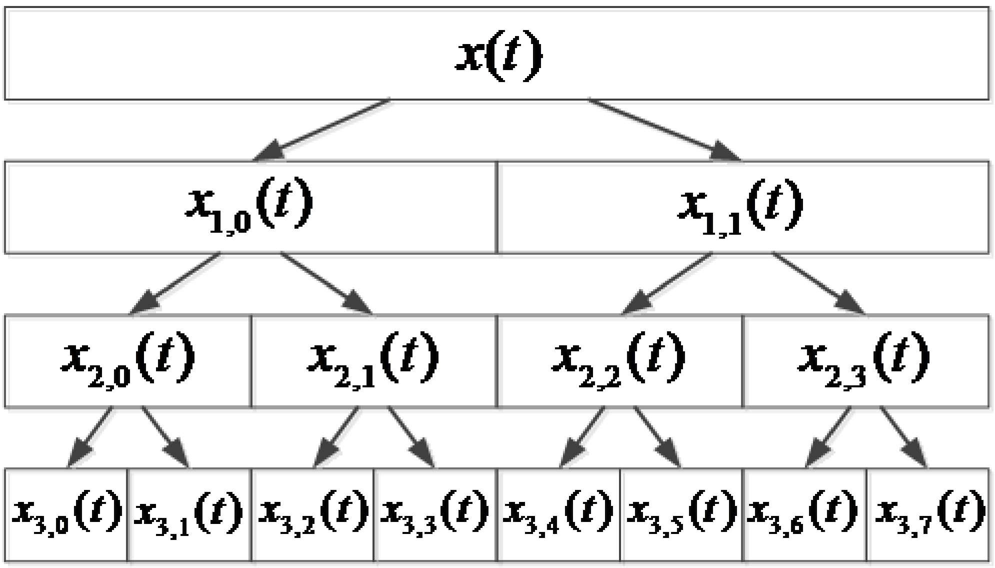

Figure 2

A three-level WPT decomposition process

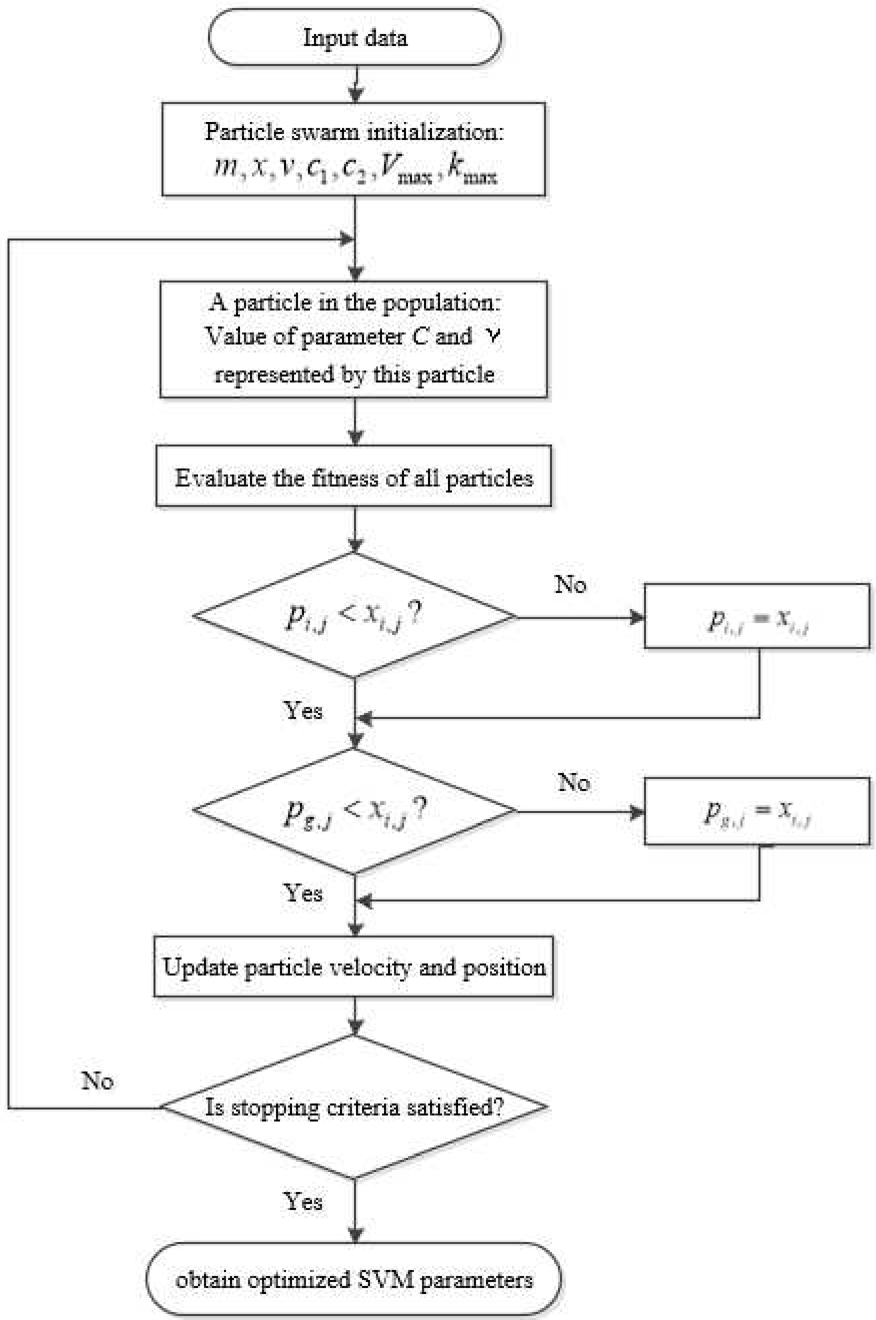

Figure 3

The procedure of optimizing the SVM parameters with PSO

Figure 4

Experimental setup

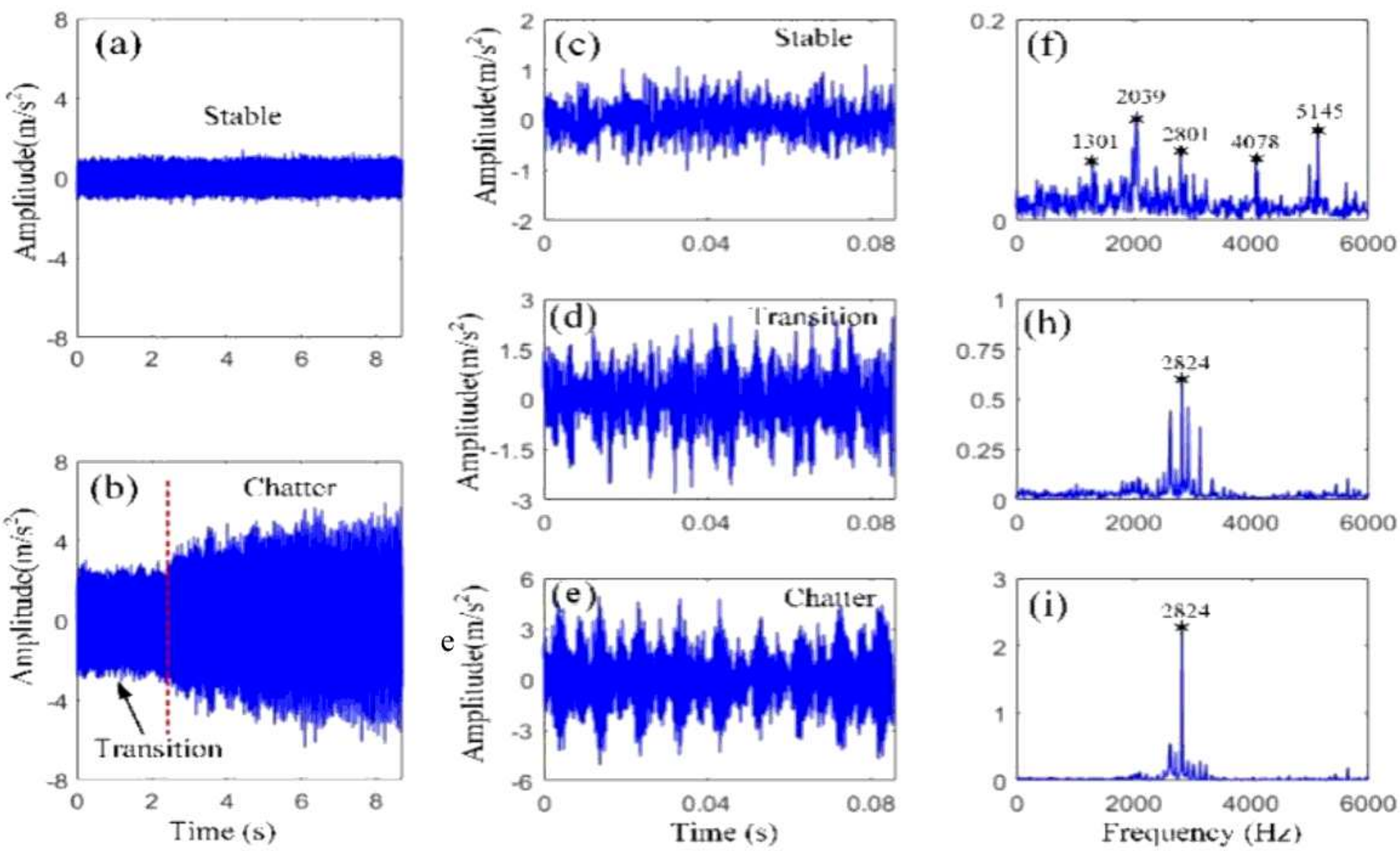

Figure 5

The measured vibration signals in three states and their FFT.

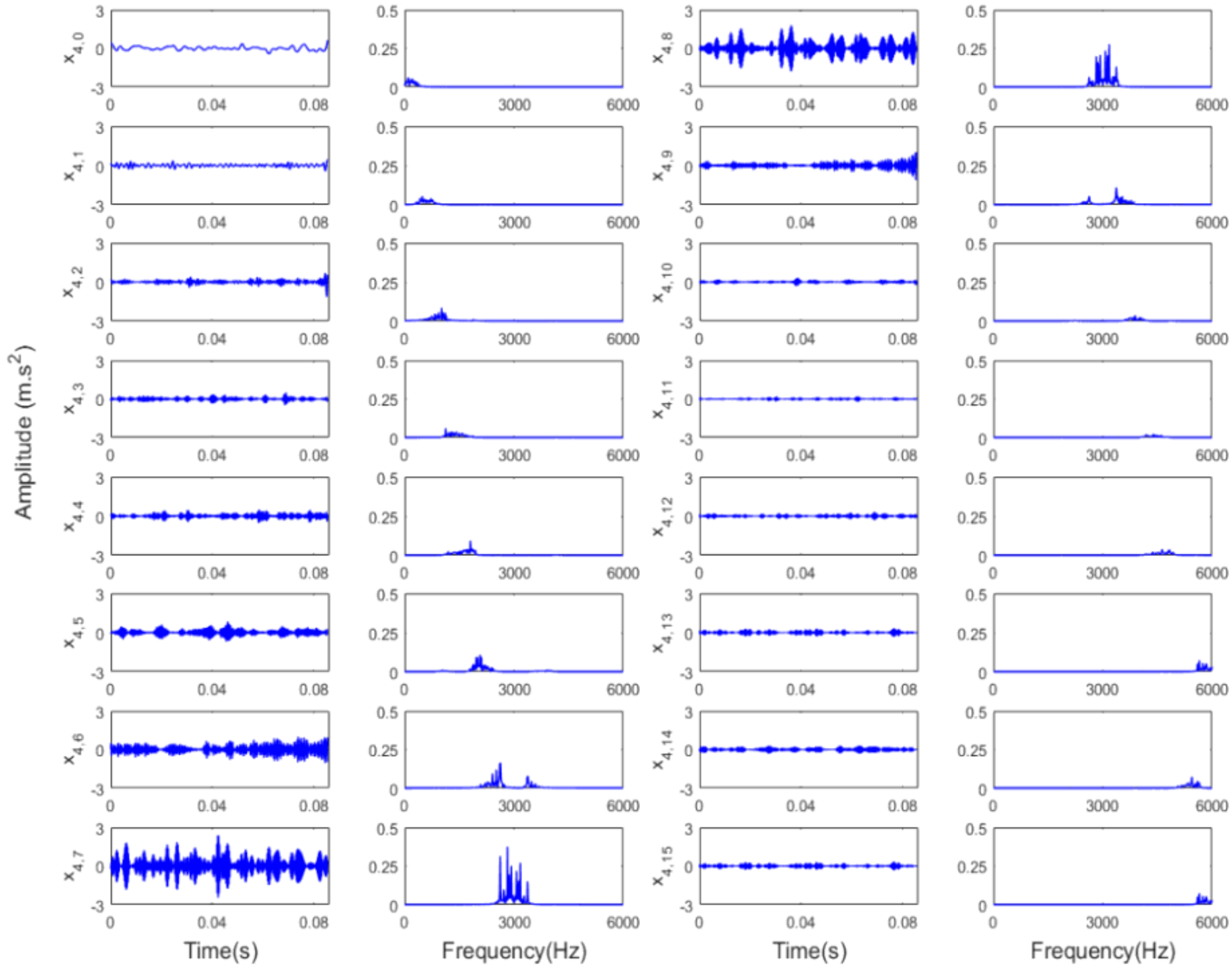

Figure 6

four-level WPT of reconstructed signal in the chatter transition state and their corresponding FFT

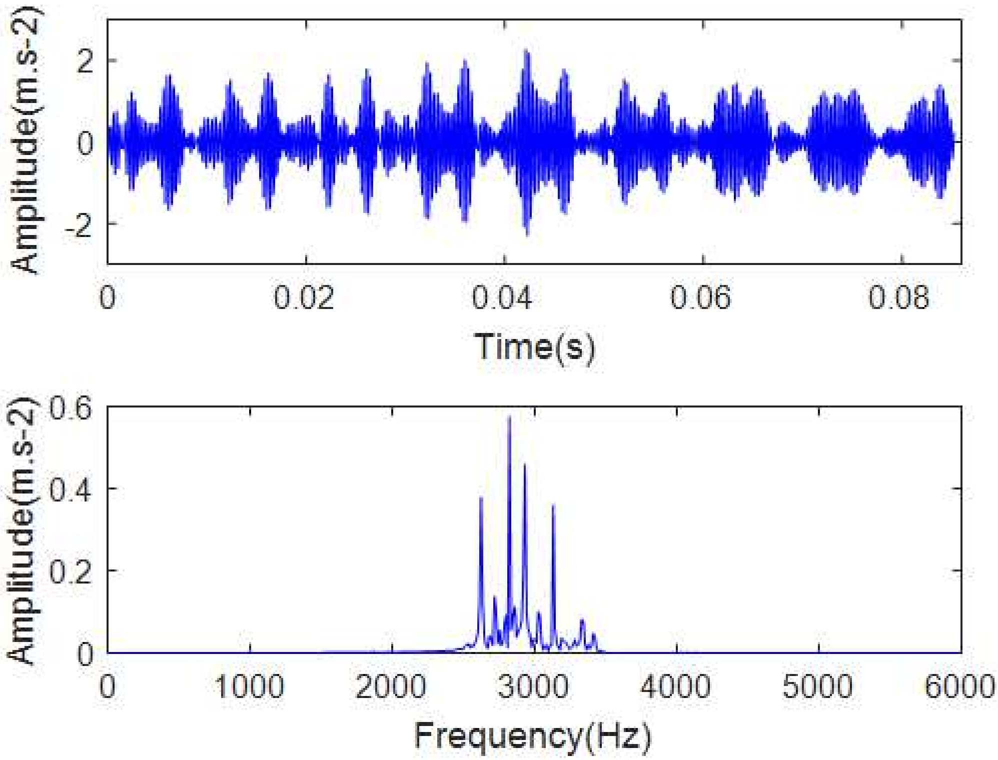

Figure 7

The reconstructed vibration signal and FFT of characteristic wavelet packets of x4,7 and x4,8 in the transition state

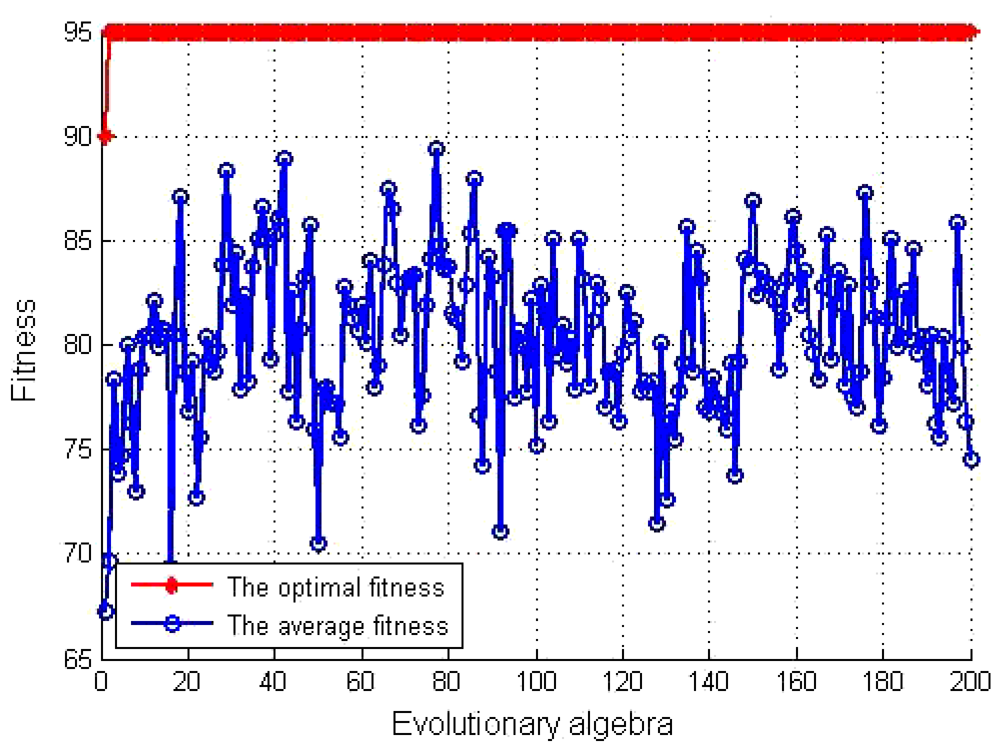

Figure 8

The adaptive evolutionary curves of PSO

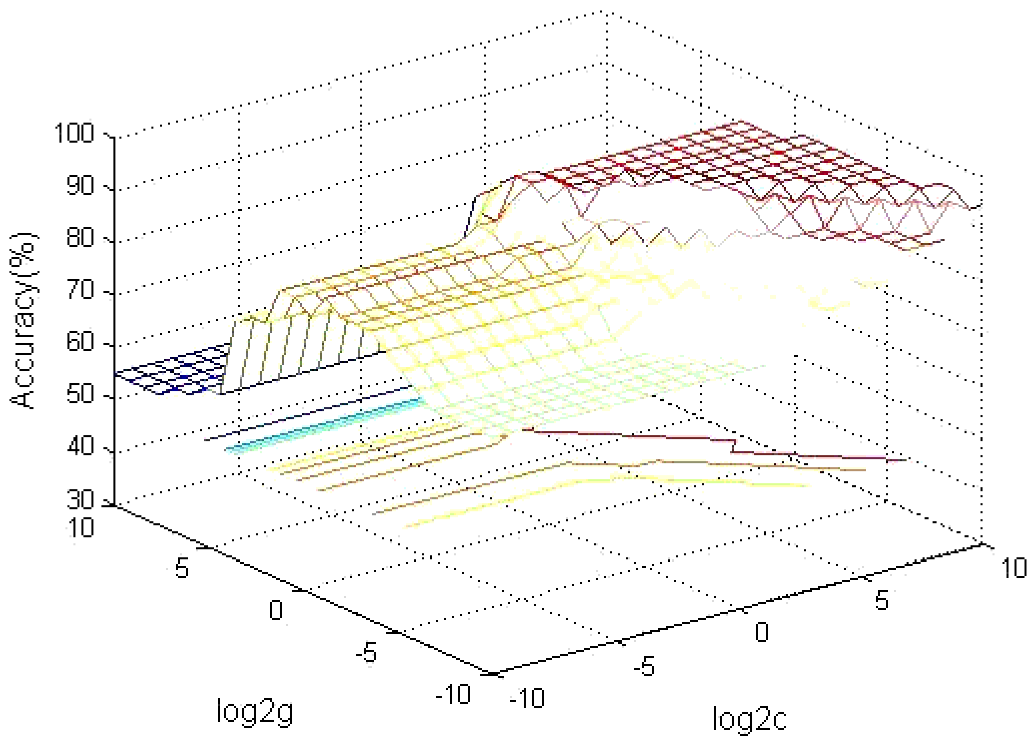

Figure 9

The classification accuracy of k-CV method

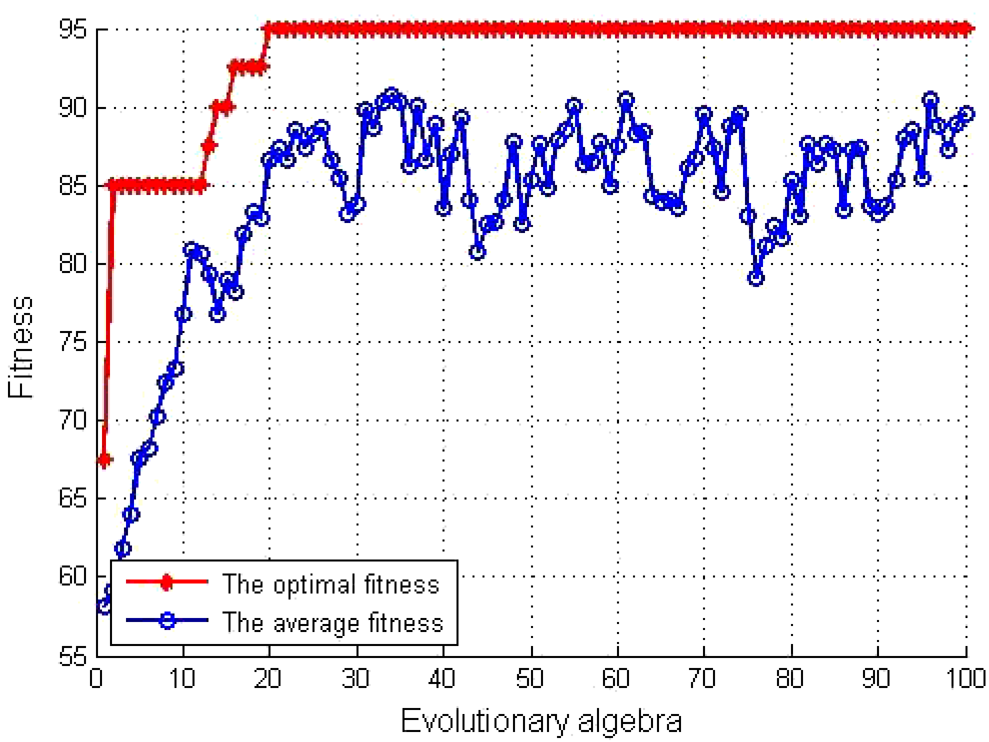

Figure 10

The adaptive evolutionary curves of GA