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A NOVEL CHATTER RECOGNITION METHOD BASED ON EMD AND SVM

Qiang SHAO[1], Xinhui WU[2], Hongying HU[3], Lin ZHENG[4], Dong WANG[5], Wenlong LI[6], Jing SU[7,*]

In this paper, a classification method is proposed based on empirical mode decomposition (EMD) and support vector machine (SVM) to improve the recognition ability of cutting chatter. The proposed method can automatically identify the chatter in cutting. Firstly, the EMD is used to decompose the chatter signal into several intrinsic mode functions. Then the relevance of the original signal is removed and main features of the component of the model function are extracted. Lastly, the SVM employed to classify the chatter. The identified ratio of EMD and SVM is compared with neural network, and PCA-SVM. The experimental results demonstrate that the proposed method can effectively identify the chatter in the cutting with the identified ratio of 95%, which is better than the other two methods.

[1] College of Mechanical and electronic Engineering, Dalian Minzu University, Dalian, 116600, China; Key laboratory of Intelligent Perception and Advanced Control of State Ethnic Affairs Commission, Dalian,116600, China
[2] College of Mechanical and electronic Engineering, Dalian Minzu University, Dalian, 116600, China; Key laboratory of Intelligent Perception and Advanced Control of State Ethnic Affairs Commission, Dalian,116600, China
[3] College of Mechanical and electronic Engineering, Dalian Minzu University, Dalian, 116600, China; Key laboratory of Intelligent Perception and Advanced Control of State Ethnic Affairs Commission, Dalian,116600, China
[4] College of Mechanical and electronic Engineering, Dalian Minzu University, Dalian, 116600, China; Key laboratory of Intelligent Perception and Advanced Control of State Ethnic Affairs Commission, Dalian,116600, China
[5] College of Mechanical and electronic Engineering, Dalian Minzu University, Dalian, 116600, China; Key laboratory of Intelligent Perception and Advanced Control of State Ethnic Affairs Commission, Dalian,116600, China
[6] College of Mechanical and electronic Engineering, Dalian Minzu University, Dalian, 116600, China; Key laboratory of Intelligent Perception and Advanced Control of State Ethnic Affairs Commission, Dalian,116600, China
[7] Key laboratory of Intelligent Perception and Advanced Control of State Ethnic Affairs Commission, Dalian,116600, China; Dalian Medical University, Affiliated Hospital 2, Epilepsy Centre, Dalian116011, China
* Corresponding Author's Email: sq@dlnu.edu.cn

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1. Introduction

Vibration during machining process is one of the key factors that affect the quality of machining and chatter is one of the most important factors in machining [1]. The results of chatter significantly impact the machining parts processing technology and processing quality. Moreover, chatter sometimes causes piercing screams, noise pollution, and even tipping, that can stop process [2-4].

The research of cutting chatter has been a focus of numerous researchers over the past several years. A number of monitoring and testing research studies have been conducted and several identification and control methods have been proposed. A novel online chatter detection method of SVM-RFE has been proposed in end milling process [5], the method is based on wavelet packet transform (WPT) and support vector machine recursive feature elimination (SVM-RFE). In [6], the problems of measurement uncertainty and recognition model uncertainty in the traditional cutting chatter recognition method have been investigated and a generalized BP neural network cutting chatter recognition model based on the generalized interval theory has been proposed. The milling chatter suppression based on the adaptive vibration reshaping has been realized in [7], which can precisely modify and control the milling vibration frequencies in frequency domain. This paper proposes a recognition method based on EMD-SVM of cutting fibrillation vibration. The EMD not only utilizes the advantages of wavelet transform multi-resolution [8], but also overcomes the difficulty of wavelet base selection in wavelet transform. In order to analyze nonlinear and non-smooth signal, the frequency instant variable signal is the most difficult. Therefore, SVM is used because it classifies the signal according to nature of the signal [9-10]. Thus, the proposed algorithm has a better recognition and resolution effect for non-smooth and nonlinear signal.

2. Signal decomposition method based on EMD

The empirical mode decomposition method first proposed by United States scholar Huang in 1996 [11-12] is a method of time-frequency signal processing. The EMD mainly analyzes and processes nonlinear and non-stationary signals. These signals are analyzed for characterization of intrinsic mode functions time scales. Each function component has a narrowband signal characteristic, and it must satisfy two conditions (IMF conditions):

1. For a signal within a limited time period, the local maximum value of the signal and the minimum point of the local envelope formed by the mean should be zero.

2. The number of extreme points in the signal sequence is either equal or different by one to the number of zero-crossing points.

The steps of modal decomposition of the signal x (t) are as follows:

① First, calculate the maxima and minima points during the limited range of the signal function x (t), and then connect by using cubic spline interpolation. The upper and the lower envelope curves of the signal are determined;

② Calculate the average of upper and lower envelope curves and mark as $m_1(t)$, then:

$$h_1(t) = x(t) - m_1(t) \tag{1}$$

③ If the function $h_1(t)$ can meet IMF conditions, obtain the first IMF component of the signal x(t). Else, regard $h_1(t)$ as the original signal, and repeat step ② until $h_{11}(t)$ is obtained:

$$h_{11}(t) = h_1(t) - m_{11}(t) \tag{2}$$

Repeat the above process k times, until h_{1k} (t) satisfies the two fundamental conditions of the IMF. Then h_{1k} (t) is represented as:

$$h_{1k}(t) = h_{1(k-1)}(t) - m_{1k}(t) \tag{3}$$

When h_{1k} (t) is almost the same as the function $h_{1(k-1)}$ (t), the function h_{1k} (t) is changed into the first intrinsic mode function as:

$$c_1(t) = h_{1k}(t) \tag{4}$$

④ Separate the function $c_1(t)$ from the original signal: $r_1(t) = s(t) - c_1(t)$, then use r_1 as a new data to be processed, repeat the above operation, and obtain the parameter c_2. Repeat the same process to obtain parameter c_n.

$$r_2 = r_1(t) - c_2(t)$$
$$r_3 = r_2(t) - c_3(t)$$
$$\ldots\ldots$$
$$r_n(t) = r_{n-1}(t) - c_n(t) \tag{5}$$

When the function r_n (t) reach a certain limit or the extreme value points are not more than two, stop disintegrating. Thus, following is obtained:

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{6}$$

$c_1(t)$, $c_2(t)$, ……, $c_n(t)$ are each modal component containing different frequency components from high to low, $r_n(t)$ is the residual component representing the tendency.

3. The classification methods of SVM

Support vector machine theory (SVM) is based on statistical learning VC dimension theory and structural risk minimization principle, which has strong generalization ability. Theoretical research shows that the selection of parameters can greatly improve the recognition rate of SVM It constructs a hyperplane in a high or infinite dimensional space and separates different class members. A machine learning method developed to solve the problem of small sample data and nonlinear classification based on optimal classification surface [13-14] is:

① Establish the optimal linear hyper plane for solving convex programming problems;

② Lead into the slack variables ξi and penalty parameter c, solved linear problems and promote SVM;

③ Adopt the nonlinear mapping method and map the sample signals from low-dimensional space to high-dimensional kernel space. Then classify according to higher-dimensional spaces optimal hyper plane to solve classification problems. Thus, optimal classification functions:

$$f(x) = sgn\{(w \cdot x + b)\} = \mathrm{sgn}\left\{ \sum_{i=1}^{n} \alpha^* y_i \left(x_i \times x + b^* \right) \right\} \tag{7}$$

In this formula, b* is the classification threshold. The resultant optimal classification planes are shown in the Fig. 1.

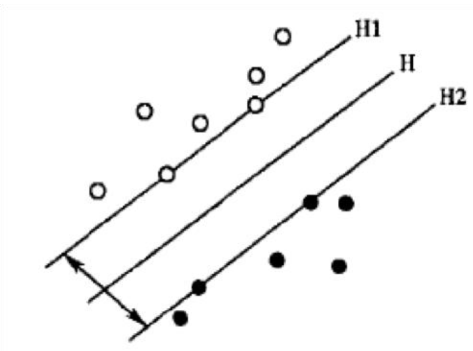

Fig.1. The optimal classification plane.

4 Chatter of the cutting experiment

4.1 Experimental conditions

The chatter of the cutting test is on the ordinary lathe (CA6140A) and the cutting conditions are as follow:

n=15~20r/s, f=0.4mm/s, ap=0.12mm, γo=8° and λs =0. The tool material YT15 is the experimental material using hardness HB243 45# normal diameter of round steel bar. The chatter recognition mode is the proposed EMD-SVM combination pattern recognition method. According to the recognition rate, the model can be used to identify the flutter in the cutting process.

During the experiment, the vibration acceleration signal a(t) is measured using an eddy current type acceleration sensor, and the dynamic cutting force F(t) is measured using YDC-III-type three-dimensional dynamometer. The signal is treated with charge amplifier and filter. The data is then entered to the computer using PCI-6023E data acquisition card. The acquisition card meets the requirements of the experiment with 16-channel, 200 KS/s frequency, 12-bit, eight DIO, and two 24-bit counters. The parameters are adjusted according to the speed of data collection and the sampling frequency is set to 128 times the rotation frequency to achieve periodic variable rate sampling.

4.2 Recognition model

The experimental process of pattern recognition is to use known data first to learn the recognition model and then use the learned model to identify the cutting chatter. Specific identification process is shown in Fig. 2.

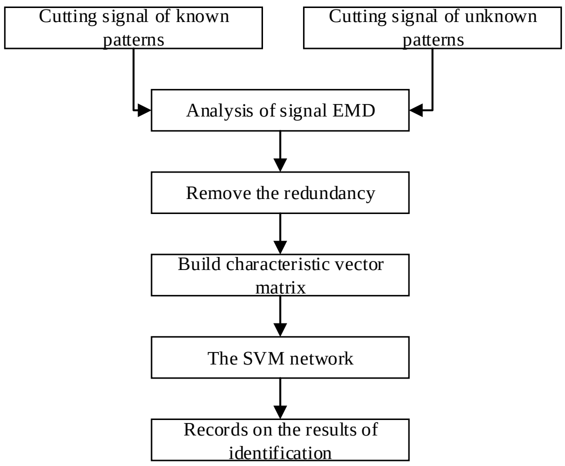

Fig. 2. Classification of cutting process flow chart.

Because the chip force signal is a non-linear non-stationary signal, EMD is used to decompose the cutting signal, make it become a stable IMF component, remove redundant items, extract its main feature parameters, and form the feature vector, which is the input of SVM classifier, and take one part of the feature vector as the training set and the other part as the test set to get the recognition accuracy of SVM classifier The IMFs energy can be calculated after the entropy of the value to determine whether chatter occurs. The energy values of entropy vary for different levels of chatter, the greater the chatter amplitude, the greater the energy entropy. The EMD decomposition is used to obtain the characteristics of the cutting signal components. SVM can effectively solve the problem of insufficient sample classification. At the same time, it is proved that the feature extraction method combining EMD and SVM modeling can well describe the features of all kinds of samples. It is advisable to use the feature vector extracted by this method as the input of classifier. Therefore, the SVM is used to classify energy entropy in order to accurately determine whether a chatter occurs.

4.3 Experimental data

Chatter is generally divided into three phases: normal cutting chatter, chatter breeds and outbreak of chatter. The experimental stages involve the acquisition of large amount of data. Fig. 3 shows the chatter of a section of data. Fig. 4 shows the components obtained after the modal decomposition of the signal shown in Fig. 3. In this experiment, the cutting force signal is used to analyze the occurrence of chatter.

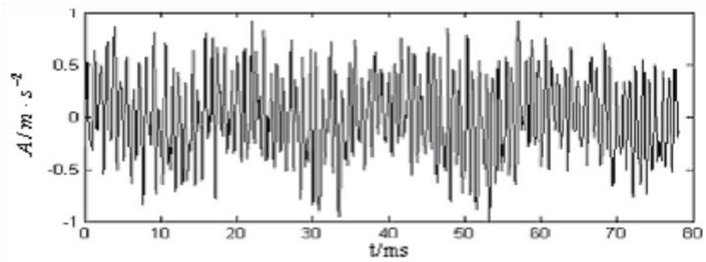

Fig. 3. The vibration signal of chatter in a moment

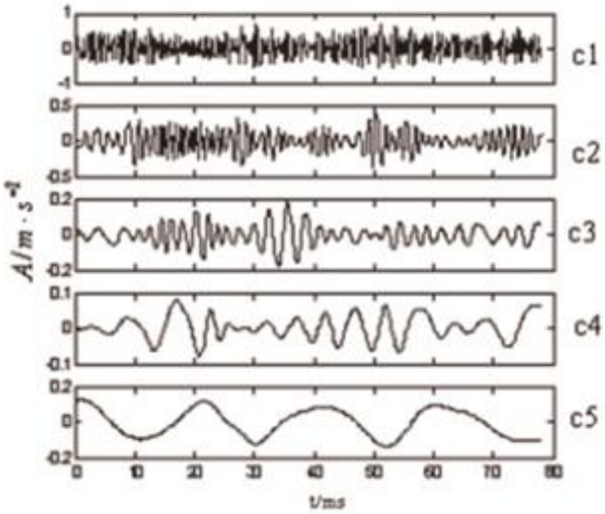

Fig. 4. Chatter mode decomposition the moment signal shown in Fig. 3.

The results of energy entropy of the partial training data in each time segment are listed in Table 1.

Table 1

The results of energy entropy of the partial training data in each time segment.

Cutting state	The sample sequence	The feature vector				
		E1	E2	E3	E4	E5
Normal cutting	1	0.261	0.106	0.062	0.033	0.011
	2	0.278	0.119	0.060	0.043	0.020
	3	0.270	0.109	0.068	0.036	0.012
Chatter breeds	1	0.512	0.274	0.131	0.065	0.027
	2	0.609	0.280	0.119	0.058	0.020
	3	0.578	0.271	0.109	0.060	0.019
Outbreak of chatter	1	0.945	0.450	0.196	0.099	0.032
	2	0.896	0.481	0.187	0.087	0.031
	3	0.912	0.476	0.198	0.091	0.029

E1, E2, E3, E4, E5 is energy entropy of each phase of the chatter. It is treated a type of feature. In the chatter experiments, the samples from each type of feature are divided forty groups. Twenty groups are used a training data to train the binary fault diagnosis model for SVM, while the other twenty groups are used to test the accuracy of classification. While training the classifier, radial basis function is used, parameter α is set to 0.015, and penalty parameter c =2. The various stages of recognition results are shown in Table 2.

Table 2

The recognition results of chatter based on EMD-SVM.

Cutting state	Number of correct diagnosis	Number of fault diagnosis	Accuracy (%)
Normal cutting	19	1	95
Chatter breeds	18	2	90
Outbreak of chatter	20	0	100

It can be seen from the Table 2 that the recognition rate can reach 95%. Moreover, every time error results are present in the flutter near the stage, there is no threshold effect exists. Thus, the proposed method has a good chatter effect.

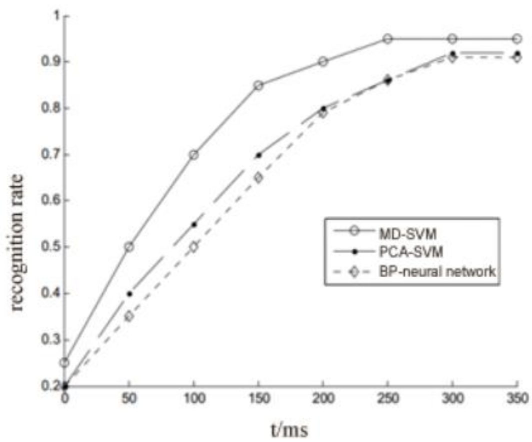

Fig. 5. The comparison of identification recognition rates of three methods.

Fig. 5 shows the comparison of the proposed method with neural networks recognition method and support vector machine recognition. It can be seen from the figure that the proposed EMD-SVM has the highest recognition rates obtained only in 250ms, which is 50ms faster than the other two methods. The proposed method not only has higher recognition rate, but also has faster convergence rate than the other two methods.

5 Conclusions

Cutting chatter directly affects the quality of products. Chatter is generally divided into three phases: normal cutting chatter, chatter breeds and outbreak of chatter. This paper proposes a recognition method of cutting chatter based on the empirical mode decomposition and support vector machine. The proposed method can detect the chatter incubation stage for timely diagnosis in order to avoid chatter, improve the cutting efficiency and provide a reliable basis. The proposed method is compared with the diagnosis method of neural networks, and principal component analysis. The comparison results demonstrate that the proposed method can effectively identify the chatter with higher accuracy and faster convergence rate than the other two methods.

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