On-line Chatter Detection Using an Improved Support Vector Machine

Changfu LIU[1], Wenxiang ZHANG[2]

(1.*School of Mechanical Engineering and Automation*, *Northeastern University*, *Shenyang* 110819, *China*;
2.*Shanghai Yu Chen Industrial Co.*, *Ltd*, *Shanghai* 201306, *China*)

Abstract: On-line chatter detection can avoid unstable cutting through monitoring the machining process. In order to identify chatter in a timely manner, an improved Support Vector Machine (SVM) is developed in this paper, based on extracted features. In the SVM model, the penalty factor (c) and the core parameter (g) have important influence on the classification, more than from Kernel Functions (KFs). Hence, first the classification results are conducted using different KFs. Then two methods are presented for exploring the best parameters. The chatter identification results show that the Genetic Algorithm (GA) approach is more suitable for deciding the parameters than the Grid Explore (GE) approach.

Key words: On-line Chatter Detection, Support Vector Machine, Parameter Optimization, Genetic Algorithms

1 Introduction

Due to the uncertainty[1, 2] of a milling process, which may involve unsuitable cutting parameters, variation of the Frequency Response Function (FRF) over time, and so on, unstable cutting may occur. Chatter will cause poor surface quality, tool wear, and low machine efficiency. Hence, measures should be taken to avoid chatter. They include selecting suitable cutting parameters according to the Lobe Stability Drawing (LSD)[3, 4] before milling, and monitoring the cutting process based on the measured signals including force[5-7], acceleration[8, 9], sound[10, 11], and current[12]. In order to realize Intelligent Manufacturing (IM), some new technologies for monitoring milling in real-time have been developed[2, 13]. These methods are suitable for industrial applications, particularly because there is no need to mount a new sensor or adjust the machine-tool.

Chatter identification can be treated as a problem of pattern classification, whose objective is to establish a mapping relationship between the chatter feature vectors and the cutting states (the stable cutting and chatter). Some previous research on chatter identification has been done by setting a suitable threshold based on experience. Recently, with the development of Artificial Intelligence (AI), some useful schemes and algorithms have been developed, such as Artificial Neural Networks (ANNs) [14, 15], Hidden Markov Model (HMM)[16] and Support Vector Machine (SVM)[17, 18], for wide application in chatter identification. Among them, SVM is an effective way to classify the cutting process. But in the mathematical model of SVM, there is a problem concerning the selection of suitable kernel function (KF) and parameters. In this paper, the classification performance of SVM is improved through GA.

The paper is organized as follows: In section 2, the mathematical model of SVM is described. Then, different KFs of SVM are investigated through experimentation. After the best KF is determined, c and g are optimized by the GE and GA, in section 4. The proposed method is verified through experiments. The conclusions of the work are drawn in section 5.

2 Mathematical Model of SVM

The basic idea of SVM is as follows: First, the input space is transformed to a high dimension space through a nonlinear transformation. Then in this high dimension space, the optimal linear classification plane is resolved. The nonlinear transformation is carried out by defining a suitable inner product function.

Different KFs are able to produce different types of nonlinear decision planes and algorithms of SVM.The common KFs are as follows:

(1) Linear KF:

$$K(x_i, x) = x_i \cdot x \quad (1)$$

(2) Polynomial KF

$$K(x_i, x) = [(x_i \cdot x) + 1]^d, \quad d = 1, 2, \cdot \cdot \cdot, n \quad (2)$$

(3) Radial Basis KF (RBF)

The most commonly used RBF is Gauss KF, which is defined as:

$$K(x_i, x) = \exp\left\{-\frac{x_i - x}{2\sigma^2}\right\} \quad (3)$$

where, x represents the center of KF, and σ represents the width of KF, which decides the range of action of the KF.

3 Chatter Identification Using SVM with Different KFs

3.1 The Chatter Identification Method

The chatter identification of the cutting states can be accomplished based on the feature vector of the cutting force. The feature vectors of the cutting forcemay be viewed as the input to SVM. Then, the cutting state diagnosis model is developed by training the model. The corresponding flowchart is presented in Fig.1.

Once the on-line chatter detection begins, the diagnosis system samples the signals in real time, and takes the extracted features (time domain features) from the Fast Fourier Transform (FFT) results as the input of the diagnosis system. In order to obtain an SVM model at a higher accuracy, an optimization method based on the GA is proposed in this paper. When compared with the optimization based on the GE, the prediction accuracy of our method outperforms the other methods.

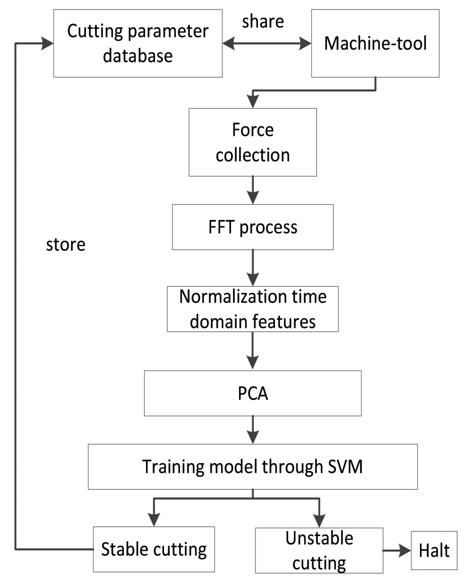

Fig. 1 The Flowchart of Milling Chatter Diagnosis.

3.2 Classification Resultsfor Different KFs

In SVM, the KFs and related parameters have an important influence on the classification result. In order to explore the influences under these different KFs, such asPolynomial KF, RBF function, Sigmoid function, the classifiers are correspondingly modeled. Among them, the penalty factor (c) and the core parameter (g) are, respectively, set to 1 and 0.25, and the other parameters are set at the default values. Then, the classification accuracy rates are compared. Table 1 presents the comparison results.

Table 1 Classification Comparisons between Different KFs.

KF	Penalty factor (c)	Core parameter (g)	Accuracy of training set	Accuracy of testing set
Polynomial	1	0.25	66.7%	54.2%
RBF	1	0.25	94.4%	79.2%
Sigmoid	1	0.25	83.3%	70.8%

As seen in Table 1, the classification accuracy with RBF exceeds the other two situations irrespective of the training set or testing set. Therefore, the SVM with RBF is more suitable for predicting the cutting states.

4 The Optimization Method of *c* and *g*

4.1 Parameter Optimization of SVM Using GE

In this paper, first the GE is employed to optimize the parameters *c* and *g* in SVM. A relatively large range is set to roughly find the best parameters. In this paper they are set as follows: the range of *c* and *g* is set to [-23, 23], and the search step of *c* and *g*, respectively, is: 0.8 and 0.6. After determining the approximate range, the range is gradually reduced according to the step size, to achieve a refined parameter selection. By gradually changing the optimization range of the parameters, the multi-group classification accuracy rate is calculated. The three-dimensional spatial distribution of the SVM classification accuracy rate is shown in Fig. 2.

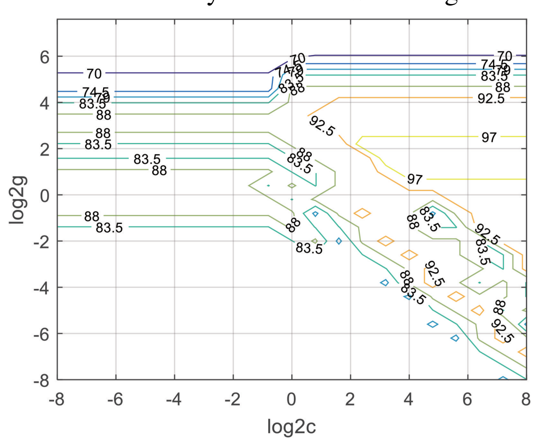

Fig. 2 The Contour Map Using GE.

4.2 Parameter Optimization of SVM Using GA

GA is a self-adaptive global optimization algorithm for searching the optimal solution, which is based on natural biological inheritance and evolutionary process. It starts with establishing a fitness function corresponding to the objective function of optimization. After that, the initial population is randomly generated and the optimal solution is provided through operations such as evaluation, selection, intersection, and variation. The detailed steps are as follows:

(a) Initialize the population: The initial population *M* containing *N* individuals is randomly generated and the number of the evolution generation is set at *T*.

(b) Set the fitness: Fitness is an indicator, which is used to evaluate the individual's quality. The fitness refers to the accuracy of the cross-validation.

(c) Select the calculator: After obtaining the fitness of the population, apply the fitness to the population. Individuals with high fitness are selected to be inherited into the next generation of population.

(d) Crossover operation: The two individuals are randomly selected in the newly generated population. Then, the part of their gene is exchanged to form a new individual.

(e) Several individuals are selected from the population to perform mutation operations through mutation probability, to change the genetics in some individuals.

(f) Termination condition judgement: If the evolutionary generation t is smaller than the biggest evolutionary generation *T*, then go to steps (b)-(e) and continue to evolve. If $t \geq T$, then the iteration ends. The individual with the biggest fitness obtained in the evolution process is viewed as the optimal solution. The parameters *c* and *g* at this time are the output, and the calculation is terminated.

The flow chart for optimizing parameters includingc and *g* in SVM using GA is shown in Fig. 3.

The parameters are set by the GA algorithm for optimization as follows: the number of populations is $N = 20$, the maximum number of iterations is 200, and the search ranges of parameters *c* and *g*are: [0.01, 100] and [0.01, 1000], 3 times cross-validation is used. The fitness curve of the iterative process through GA algorithm is shown in Fig. 4.

It can be seen from Figure 4 that the average fitness of the parameter optimization in the SVM using the GA is above 80%, and the optimal fitness value is obtained near the 22th generation by continuously

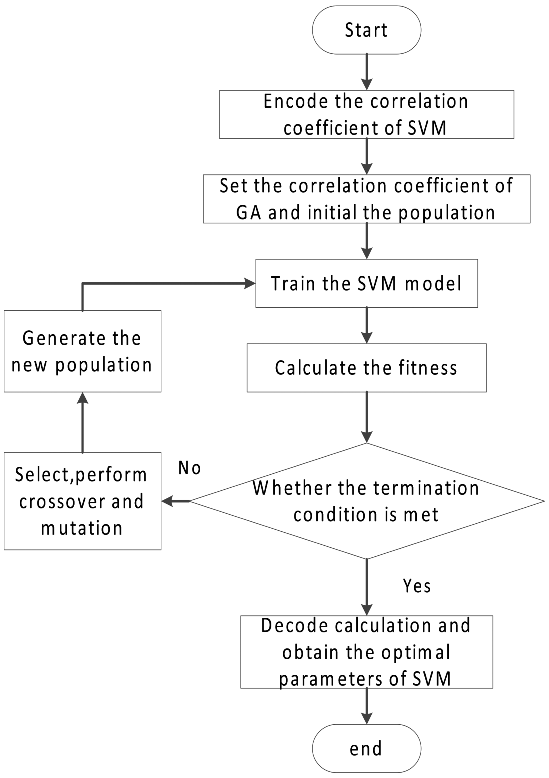

Fig. 3 Optimization of SVM Parameters Based on GA Algorithm.

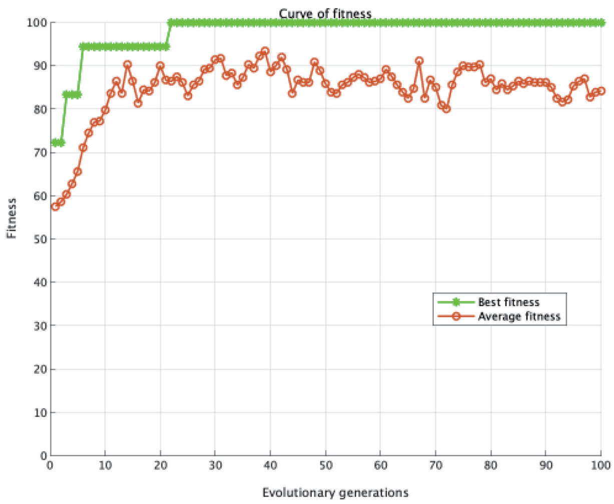

Fig. 4 Fitness Optimization Using GA.

performing the iterative update calculation. Then, $c = 13.3717$ and $g = 1.6083$.

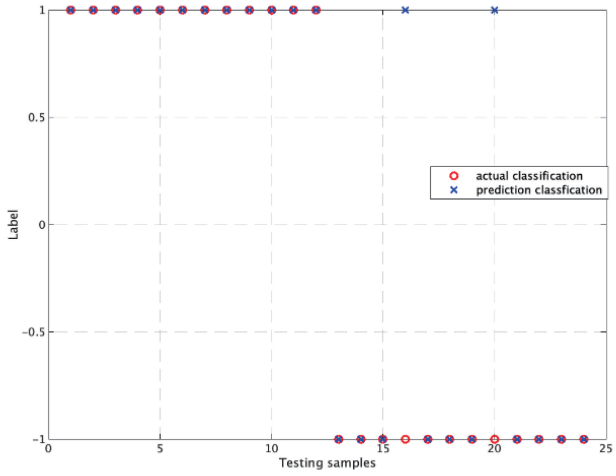

Fig. 5 The Prediction Result of the Testing Set Using Genetic Algorithm.

The optimal parameters obtained by the GA are used to analyze the training set and the testing set. The simulation results are shown in Fig. 5. It can be calculated that the classification accuracy of the testing set is 90.9%. Among them, 2 testing samples are diagnosed with errors and they are misdiagnosed as stable states. A comparison is made between different optimization methods, in Table 2.

Table 2 presents the parameter setting and classification results using two optimization methods and no optimization method. Among them, there is a prediction accuracy improvement using the optimization methods, irrespective of GE or GA. However, GA is able to realize the highest accuracy. The accuracy of the training set is 100% and the accuracy of the testing set reaches 90.9%, which considerably exceeds those of the other two optimization methods. But in order to find the best c and g, it has to consume a much longer time.

Table 2 Different Optimization Methods for SVM Classification Diagnostic Results.

Optimization method	Consumed time	c	g	Accuracy of the training set	Accuracy of the testing set
No	0.46s	1.0	0.25	94.4%	77.3%
GE	1.95	5.278	3.7321	100%	81.8%
GA	4.27	13.3717	1.6083	100%	90.9%

5 Conclusion

In this paper, an improved SVM was proposed to classify the cutting process through finding suitable KFs and parameters. In the SVM model, c and g had a more important influence for the classification compared to KFs. They were investigated to show their affluence on the SVM. The results showed that the RBF had a more accurate prediction compared to the other KFs. Based on the determined KF, the GE and GA were used to optimize the SVM. Compared to the GE, the classification accuracy of the GA was superior to the classification accuracy of the GE. In this paper, a higher classification accuracy for cutting states was achieved without introducing a new classification model.

References

[1] Caliskan, Hakan, Kilic, Zekai Murat, Altintas, Yusuf. (2018). On-Line Energy-Based Milling Chatter Detection. Journal of Manufacturing Science and Engineering, 140(11), pp. 111012.

[2] Aslan, Deniz, Altintas, Yusuf. (2018). On-line chatter detection in milling using drive motor current commands extracted from CNC. International Journal of Machine Tools and Manufacture, 132pp. 64-80.

[3] Altintas, Yusuf. (2012). Manufacturing Automation: Metal Cutting Mechanics, Machine Tool Vibrations, and CNC Design. Cambridge: University Press, pp20-48.

[4] Wan, Min, Altintas, Yusuf. (2014). Mechanics and dynamics of thread milling process. International Journal of Machine Tools and Manufacture, 87pp. 16-26.

[5] Liu, Changfu, Zhu, Lida, Ni, Chenbing. (2018). Chatter detection in milling process based on VMD and energy entropy. Mechanical Systems & Signal Processing, 105pp. 169-182.

[6] Liu, Changfu, Zhu, Lida, Ni, Chenbing. (2017). The chatter identification in end milling based on combining EMD and WPD. International Journal of Advanced Manufacturing Technology, 91(9-12), pp. 3339-3348.

[7] Pérez-Canales, Daniel, Vela-Martínezc, Luciano, Alvarez-Ramirezb, Jose. (2012). Analysis of the entropy randomness index for machining chatter detection. International Journal of Machine Tools & Manufacture, 62(1), pp. 39-45.

[8] Vela-Martínez, Luciano, Jauregui-Correa, Juan Carlos, Rodriguez, Eduardo, et al. (2010). Using detrended fluctuation analysis to monitor chattering in cutter tool machines. International Journal of Machine Tools & Manufacture, 50(7), pp. 651-657.

[9] Lamraoui, M, Thomas, Marc, El Badaoui, M. (2014). Cyclostationarity approach for monitoring chatter and tool wear in high speed milling. Mechanical Systems and Signal Processing, 44(1-2), pp. 177-198.

[10] Thaler, Tilen, Poto nik, Primož, Bric, Ivan, et al. (2014). Chatter detection in band sawing based on discriminant analysis of sound features. Applied Acoustics, 77(77), pp. 114-121.

[11] Cao, Hongrui, Yue, Yiting, Chen, Xuefeng, et al. (2017). Chatter detection in milling process based on synchrosqueezing transform of sound signals. The International Journal of Advanced Manufacturing Technology, 89(9-12), pp. 2747-2755.

[12] Yang, Zhi Gang, Liu, Hong Qi, Li, Bin, et al. (2011). Recognition of chatter in boring operations using spindle motor current. In: International Conference on Transportation, Mechanical, and Electrical Engineering. [online] Changchun: NCTT, pp2158-2161. Available at: https://ieeexplore.ieee.org/document/6199646.[Acessed 14 May. 2012].

[13] Luo, Ming, Luo, Huan, Axinte, Dragos, et al. (2018). A wireless instrumented milling cutter system with embedded PVDF sensors. Mechanical Systems and Signal Processing, 110pp. 556-568.

[14] Shrivastava, Y, Singh, B. (2018). Possible way to diminish the effect of chatter in CNC turning based on EMD and ANN approaches. Arabian Journal for Science and Engineering, 43(9), pp. 4571-4591.

[15] Lamraoui, Mourad, Barakat, Mustapha, Thomas, Marc, et al. (2015). Chatter detection in milling machines by neural network classification and feature selection. Journal of Vibration and Control, 21(7), pp. 1251-1266.

[16] Han, Zhenyu, Jin, Hongyu, Han, Dedong, et al. (2017). ESPRIT-and HMM-based real-time monitoring and suppression of machining chatter in smart CNC milling system. The International Journal of Advanced Manufacturing Technology, 89(9-12), pp.

2731-2746.

[17] Lamraoui, M, El Badaoui, M, Guillet, F. (2015). Chatter detection in CNC milling processes based on Wiener-SVM approach and using only motor current signals. In: Vibration Engineering and Technology of Machinery. [online] Cham: NCTT, pp567-578. Available at: https://doi.org/10.1007/978-3-319-09918-7_50.[Acessed 15 August. 2014].

[18] Srinivasan, Amrita, Dornfeld, David, Bhinge, Raunak. (2016). Integrated vibration and acoustic data fusion for chatter and tool condition classification in milling. In: 2016 International Symposium on Flexible Automation (ISFA). [online] Cleveland: NCTT, pp263-266. Available at:10.1109/ISFA.2016.7790172.[Acessed 19 December. 2016].