Tool Wear State Recognition Based on Machine Learning

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Abstract: In order to quickly identify the current state of tool wear in real time, the standard of tool wear state division is analyzed first. The machine learning methods commonly used for pattern recognition classification including SVM, ANN, random forest and so on. In this paper, tool wear data sets are used to build a variety of machine learning models using the constructed feature space. LVQ, random forest and SVM are used to monitor the wear state respectively, and the classification accuracy of the classification model on the test set is calculated respectively.

Key words: LVQ; Random Forest; SVM; Machine Learning State

1. Cutting Tool Wear State Classification Standard

The c1, c4 and c6 milling cutters used in this paper are 108mm long and 0.2mm deep for each cutting tool. The three slotted wear process curves of the three milling cutters were drawn respectively for comparison. It was found that the wear trend of the three milling cutters was roughly the same, and the wear process of c4 had better generalization performance and was more representative. Therefore, only the three slotted wear process curves of c4 were shown in Figure 1 below. In Figure 1, it can be clearly seen that milling cutter 4 is very close to the 3 stages divided by the whole tool wear process in the introduction[1]. The tool has a period of intense wear but shorter run- in period at the beginning of use, that is, the initial wear stage; Next, when the run- in tool continues to process, due to the reduction of friction resistance, it will experience a long-term slow and continuous normal wear stage; Finally, due to the long-term use of the tool and blunt resulting in the tool to continue cutting the friction pressure increases, at this time the tool ushered in a rapid rise in the amount of wear of the sharp wear stage. In the process of tool processing, the tool should be replaced in time before the wear state enters sharp wear to ensure the quality of the workpiece and the normal operation of the processing process. Therefore, choose the milling cutter 4 wear amount as the wear state division standard. As shown in Figure 1 below.

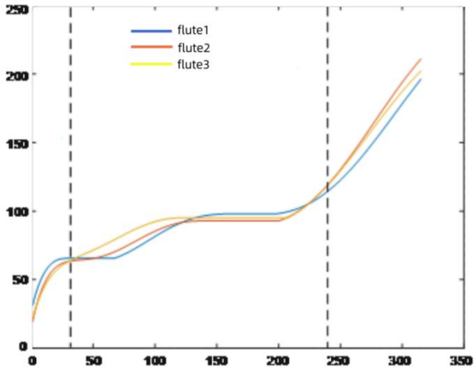

Figure 1. Wear Process Curve of Milling Cutter 4

According to the changes in the wear values of the three groove directions of the milling cutter 4, it is divided into three different tool wear states, and the range of tool travel times corresponding to each wear state is found. Table 1 is listed as the basis for establishing the tool wear state recognition model and training.

Table1. Comparison Table of Different Tool Wear States and Tool Travel Times

Wear value (mm)	Tool wear state	Number of knife walks (times)
[0,0.07)	Initial wear	[1, 30]
[0.07, 0.115)	Normal wear and tear	[31, 240]
[0.115, + up)	Sharp wear	[241, 315]

2. Principle Introduction

2.1 Learning Vector Quantization Neurall Network

Learning Vector Quantization is a kind of forward network that has supervised learning and achieves the final goal by training the competitive layer.

LVQ network is composed of three simple layers of neurons, namely the input layer, the competition layer and the linear output layer. Its structure is shown in Figure 2 below. There are fewer neurons in the linear output layer than in the competition layer. The relationship between the competition layer and the linear output layer is many-to-one, and the connection weight between the two layers is always 1.

LVQ neural network learning algorithm is as follows[2]:

(1) Initialize the weight w_{ij} and learning rate.

(2)The distance between the input layer vector and the neurons in the competition layer is obtained according to the formula.

$$d_i = \sqrt{\sum_{j=1}^{R}(x_i - w_{ij})^2} \quad i = 1,2,\cdots,S^1 \tag{1}$$

(3) Find the neuron with the smallest distance calculated in the competition layer, and attach the class label to the neuron connected to the output layer d_i C_i.

(4) The real class label corresponding to the input vector is, if, the weight adjustment is completed according to formula (2), otherwise, the adjustment is made according to formula (3).

$$w_{ij\_new} = w_{ij\_old} + \eta(x - w_{ij\_old}) \tag{2}$$

$$w_{ij\_new} = w_{ij\_old} - \eta(x - w_{ij\_old}) \tag{3}$$

LVQ network structure is simple, for complex classification work not only does not need to carry out standard orthogonalization of the input, but a lso simply calculates the distance between the first two layers of the network and relies on the interaction of internal units to achieve.

2.2 Random Forest Theory

Random Forest (RF) is a classifier composed of multiple decision trees, which have no correlation and are generated randomly [49]. When the input vector is put into RF, each decision tree completes the classification operation independently, and the final output category of RF takes the classification mode label of all trees. The specific steps of the algorithm are as follows[3]:

(1)For the entire training sample of the input model, the Booststrap resampling method is used to randomly generate K sub-training sets S1,S2,...,SK.

(2)A subtraining set Si generates a corresponding decision tree Ci, and a total of K corresponding decision trees are generated; When splitting feature set is selected by each internal node, the best splitting method of M features randomly selected from the whole feature space m is used to split the node.

(3)Complete growth of each tree without pruning.

(4)Each decision tree is tested separately on the input test set data X, and the category C1(X) corresponding to each tree is obtained..,CK(X).

(5)The voting method selects the category that appears most frequently in K trees and takes it as the output category of test set X.

3. Model Test Results

3.1 Tool Wear State Recognition Based on LVQ Model

The tool wear state recognition based on machine learning model is applied to the milling cutter wear data set used in this paper, from the acquisition of original data, to data preprocessing, feature extraction, label generation, to the establishment of learning vector quantization model and random forest model, to the final test set recognition results and model comparison evaluation.

The learning vector quantization neural network was established and the model training parameters were set according to Table 2. First, label the divided tool wear state. Set sample label 0 to indicate initial wear, 1 to indicate normal wear and 2 to indicate sharp wear. The sample division of training set and test set is shown in Table 3 below. First, the labels were processed by one-time thermal coding as shown in Table 3, and then c1 with labels and its feature space were input as the training set to train the established LVQ model. c4 and c6 are used as test sets, and their feature data sets are input into the trained model for wear state recognition. The recognition results are used as the evaluation criteria for LVQ model recognition performance.

In this paper, after the status labels of milling cutters 1 and 4 are calibrated according to the wear standard, the size of the training set is 315×32, the size of the test set is 630×32, and the classification results of the tool wear state obtained by the LVQ model for test set c4 are respectively shown in Figure 2. The overall classification accuracy of test set 4 is 93.02% respectively.

Table 2. Parameter Settings of LVQ Neural Network

Number of competing layer neurons	Weight learning function	Maximum number of training	Learning rate
20	learnlv2	200	0.01

Table 3. Sample Division and Wear Status Label Conversion Table

	Labels	Therml coding	Number of training set samples	Number of test set samples
Initial wear	0	100	30	60
Normal wear	1	010	210	420
Sharp wear	2	001	75	150

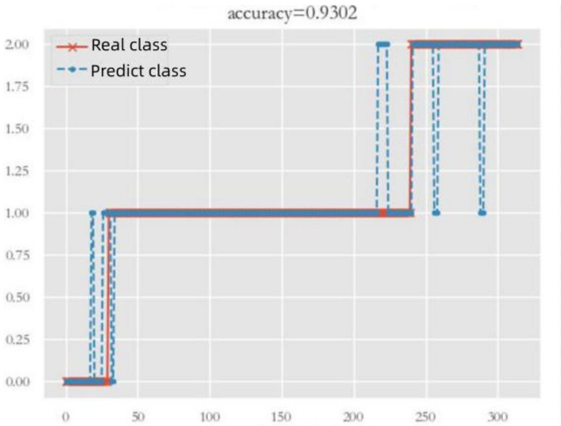

Figure 2. LVQ Classification Results of Test Set

3.2 Recognition of Tool Wear State Based on RF Model

First, the original data of tools 1 and 4 were preprocessed, feature extraction and feature selection to form a feature space of 315×32. Then c1 with state label was input into the random forest model as a training set (size 315×32) for training. Finally, tool 4 (size 630×32) was put into the trained RF model for classification and prediction. The classification results of tool wear state of test set 4 were shown in Figure 3. The overall classification accuracy was 93.65% respectively.

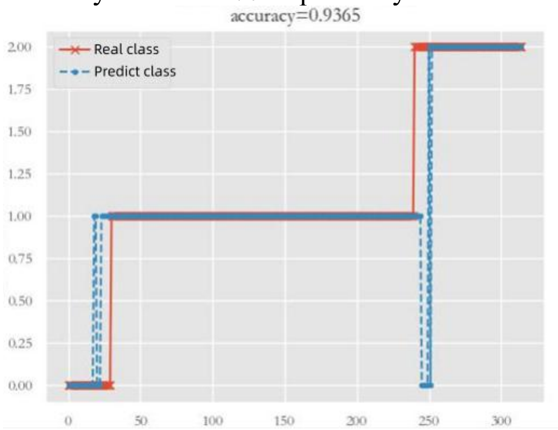

Figure 3. Test Set Tool 4 Random Forest Classification Results

3.3 Recognition of Tool Wear State Based on SVM Model

SVM is a machine learning model commonly used for classification. Here, as a comparison between LVQ model and RF model, SVM is applied to the data set used in this paper to complete the wear state recognition. The same milling cutter 1 was input into the SVM model as a training set for training, and then tool 4 was put into the trained SVM model for state classification. The classification results of tool wear state of test set 4 were shown in Figure 4, and the classification accuracy was 87.62% respectively.

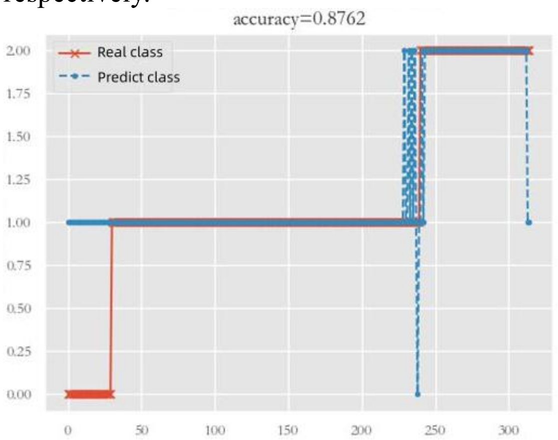

Figure 4. SVM Classification Results of Tool 4 in Test Set

4. Conclusion

This paper briefly introduces the machine learning model for tool wear state recognition, uses the constructed feature space to build a variety of machine learning models: LVQ, random forest and SVM respectively carry out wear state monitoring, and carry out state classification on the milling cutter wear test set, and obtain the classification accuracy of each model.

References

[1] Tönshoff H K, Wulfsberg J P, Kals H J J, et al. Developments and trends in monitoring and control of machining processes[J]. CIRP Annals, 1988, 37(2): 611-622.

[2] Rehorn A G, Jiang J, Orban P E. State-of-the-art methods and results in tool condition monitoring: a review[J]. The International Journal of Advanced Manufacturing Technology, 2005, 26(7-8): 693-710.

[3] Tlusty J, Andrews G C. A critical review of sensors for unmanned machining[J]. CIRP annals, 1983, 32(2): 563-572.