Modeling for Robot Grinding Process Based on LS-SVM

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Keywords: robot grinding; LS-SVM; regression; modeling

Abstract. Grinding Process Modeling has a great influence on the machining accuracy of robot grinding. Due to the high coupling and the nonlinearity, it is very difficult to model robot grinding process by grinding mechanism. In this paper, a regression prediction method based on Least Squares Support Vector Machines (LS-SVM) is proposed for modeling robot grinding process. By analyzing observed variables and utilizing the LS-SVM algorithm, we build a regression model to predict the grinding removal. Experimental results demonstrate that our method can achieve a high prediction accuracy, which basically meets practical processing demands.

Introduction

With the development of automation technology, the robot is used more and more widely in the field of grinding process. Compared with traditional manual grinding and machine-tool grinding, robot grinding has advantages in flexibility, generality and extendibility. At present, one of main research directions on robot grinding is to improve its machining accuracy, which mainly depends on the control of grinding removal. For robot grinding, the relationship between feed rate and grinding removal are very complex, and under the technique conditions in existence, it is unable to obtain the feedback of grinding removal by online real-time measurements. Thus, it is very difficult to control grinding removal directly. To tackle this problem, we need to build a robot grinding process model, in which observed variables are input and grinding removal is output.

There are many methods for modeling grinding process, such as empirical modeling [1], theoretical modeling [2] and finite element simulation. The establishment of an empirical model depends on a large amount of experimental data and the prediction accuracy rests with the size of the sample space, which brings a high model building cost. The cost of a theoretical model is relatively low, but various kinetic parameters have complex influences on grinding process. Thus, it is very difficult to model grinding process by grinding mechanism. For finite element simulation, limited by computational complexity, it is usually used only for analyzing a small amount of abrasive particles. To address these problems, a regression prediction method based on Least Squares Support Vector Machines (LS-SVM) [3] is proposed for modeling robot grinding process. This method avoids analyzing dynamic parameters one by one. As an effective regression algorithm, LS-SVM can automatically find the complex nonlinear relationship between observed variables and grinding removal. The grinding and the regression modeling for blades validate the effectiveness of this method.

Principle of Regression and LS-SVM

Regression analysis is a predictive modeling technique, which studies the relationship between the variable (target) and the independent variable (predictor). It is usually used for prediction analysis, time series model, and discovering causal relationship between variables. There are many widely-used regression algorithms, such as Linear Regression, Neural Network Regression, Logistic Regression.

With the development of regression analysis technology, Vapnik et al. proposed Support Vector Machines (SVM) [4], which uses kernel functions to transform linear inseparable samples in a low dimensional input space into a high dimensional feature space to make them linear separable. To improve the performance and the efficiency of SVM, Suykens et al. proposed Least Squares Support Vector Machines (LS-SVM). LS-SVM replaces the relaxation variable in the traditional SVM by the square of the error, and then its objective function is as following

$$\min_{w,b,e} J_P(w,e) = \frac{1}{2}w^T w + \gamma \frac{1}{2}\sum_{k=1}^{N} e_k^2 \tag{1}$$

$$such\ that\ \ y_k = w^T \varphi(x_k) + b + e_k, k = 1, \ldots, N \tag{2}$$

By this objective function, the inequality constraint in the traditional SVM is change to an equality constraint, which greatly simplifies the complexity of the calculation and improves the calculation speed.

Use the Lagrange function method to transform the objective function into a quadratic programming problem

$$L(w,b,e;\alpha) = J_p(w,e) - \sum_{k=1}^{N} \alpha_k \{w^T \varphi(x_k) + b + e_k - y_k\} \tag{3}$$

where α is the Lagrange multiplier. Optimization conditions are

$$\begin{cases} \dfrac{\partial L}{\partial w} = 0 \ \rightarrow \ w = \sum_{k=1}^{N} a_k \varphi(x_k) \\ \dfrac{\partial L}{\partial b} = 0 \ \rightarrow \ \sum_{k=1}^{N} a_k = 0 \\ \dfrac{\partial L}{\partial e_k} = 0 \ \rightarrow \ a_k = \gamma e_k \quad\ k = 1, \ldots, N \\ \dfrac{\partial L}{\partial a_k} = 0 \rightarrow \ w^T \varphi(x_k) + b + e_k - y_k = 0 \end{cases} \tag{4}$$

α and b can be obtain by solving the above equations.

The nonlinear regression function of LS-SVM is as following

$$y(x) = \sum_{k=1}^{N} a_k K(x, x_k) + b \tag{5}$$

The advantage of LS-SVM is that it is based on the principle of structural risk minimization. It has strong generalization ability and can avoid falling into local minima. Moreover, compared with other regression algorithm, the number of samples required for LS-SVM is less, which make it especially suitable for small sample training.

Modeling the Robot Grinding Process based on LS-SVM

To build a LS-SVM prediction model, firstly, the input features and the output feature of LS-SVM are needed to be selected. The output feature is easy to be determined: it is grinding removal. The choice of the input features is commonly according to experience. Regression analysis, it is unnecessary to use all observable variables as input features. Some variables are redundant or have little correlations with output. The extra variable will increase the dimension of input features, resulting in increasing a lot of unnecessary computation and decreasing modeling speed. Several main variables can make sure a high prediction accuracy of LS-SVM and other secondary variables can be ignored. For the robot grinding process, the three controllable parameters, contact force, the feed rate of the robot, and the surface curvature of the artifact, have very obvious effects on the grinding quantity. Experiments show that there exists a function relationship between the three controllable parameters and grinding removal. Thus, in this paper, the three controllable parameters are selected as the input features of LS-SVM.

The prediction accuracy is also depending on the choices of the model parameters of LS-SVM. There are two model parameters needed to be regulated, which are regularization factor *C* and kernel function. *C* is used to balance the empirical risk and the extension ability of LS-SVM. If the value of *C* is small, the prediction error penalty is small, resulting in large training errors; If the value of *C* is large, although LS-SVM can obtain less experience risk, its model extension ability decreases. Kernel function has a critical impact on the performance of LS-SVM, especially for processing linear inseparable data. There are four frequently-used kernel functions: the linear kernel function, the polynomial kernel function, the RBF kernel function and the sigmoid kernel function. The linear kernel is mainly used for processing linear separable data. The polynomial kernel function can map data from a low dimensional feature space to a high dimensional feature space. But when the order of the polynomial is relatively high, the element value of the kernel matrix will tend to infinity or infinitesimal. The RBF kernel function a kind of kernel function with strong locality. It performances well on both large and small data. The sigmoid kernel function can transform SVM into multi-layer neural networks. The optimal choices of *C* and kernel function are determined by grid search and cross validation.

Experiments

The training and test data is obtained from the grinding process of a metal blade. For a calibrated robot grinding system, first set the track of the robot grinding, then change the contact force and the feed rate of the robot, and repeat grinding the same work piece. In the experiment, to ensure that the force and the speed required by processing have the experimental data distribution in the limited range, the values of the contact force and the feed rate should meet a certain distribution. Based on the practical experience, the contact force is set ranging from 25 N to 75 N, with a 5N sampling interval, and the feed rate is set ranging from 10 cm/s to 40 cm/s, with a sampling interval.

Based on the experimental data, LibSVM [5] is used to build a LS-SVM regression model for the robot grinding process. In the training process, the parameter *C* is set as 12, the parameter *S* is set as 4 and the parameter *T* is set ranging from 0-3. Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) are used to evaluate the performance of the model. Table 1 shows the prediction results of the LS-SVM model with different kernel functions. Fig. 1 shows the comparison between real values and prediction values of RBF LS-SVM.

The results show that LS-SVM can model the robot grinding process well. Among all the kernel functions, the RBF kernel function achieves the best result. The prediction accuracy of the RBF LS-SVM is above 95%.

Table 1. Results of prediction

Model	RMSE (mm)	MAPE (%)
Linear LS-SVM	0.015	0.071
Polynomial LS-SVM	0.0113	0.053
RBF LS-SVM	0.0086	0.042
Sigmoid LS-SVM	0.0097	0.046

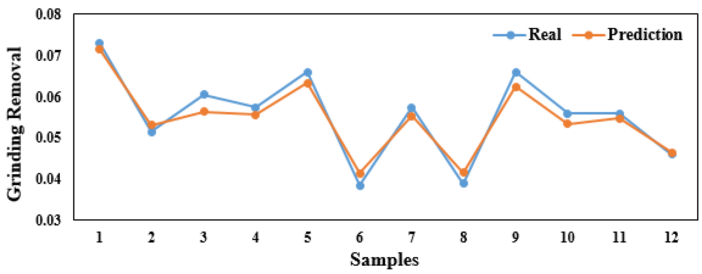

Fig.1. Comparison between real values and prediction values of RBF LS-SVM

Summary

In this paper, LS-SVM is used to tackle the difficulties in robot grinding process modeling. Based on actual experimental data, a LS-SVM regression model is built to predict the grinding removal. The contact force, the feed rate of the robot, and the surface curvature of the artifact are selected as input features of the model. The influences of different parameters, regularization factor and kernel function, are also researched. Experimental results demonstrate that the LS-SVM model can achieve a high prediction accuracy, which basically meets practical processing demands.

Acknowledgements

This project is supported by National Natural Science Foundation of China (Grant No. 51475270)

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