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RESEARCH ARTICLE

Study on Temperature Measurement Point Optimization and Thermal Error Modeling of NC Machine Tools

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Abstract:

Background:

In precision machining, thermal error is the main source of machine tool error. And thermal error compensation is an effective method to reduce thermal error.

Objective:

In order to improve the prediction accuracy and computational efficiency of thermal error model, a new optimization method used for the selection of temperature measurement point is proposed.

Method:

This method is based on stepwise regression. According to the results of partial-F statistic, new variable is selected one by one, unapparent variables are deleted, and optimization selection of temperature measurement point is fulfilled, thermal error model of the NC machine tool is presented.

Result:

The new modeling method was used on NC machine tool, which reduced the temperature point number from 24 to 5. Moreover, model residual was less than 5μm after compensation.

Conclusion:

The result shows that the new thermal error model has higher prediction accuracy and less temperature variables.

Keywords: NC machine tool, Stepwise regression method, Measurement point optimization, Thermal error modeling.

1. INTRODUCTION

Thermal error compensation technique of NC machine tools is an important approach to improve the machining accuracy, and thermal error modeling is the basis of compensation. It is recognized that thermal error model which has high accuracy and high robustness is the key to improve the manufacturing level and international competitiveness, which can be found in many research achievements. Nowadays, researchers are still working on it [1 - 5].

Compared with artificial intelligence models, such as NN (neural networks) [6, 7] and GA (genetic algorithm) [8, 9] *etc*, thermal error models based on different regression theories have advantages of easy calculation, strong practicality, and model parameters can be displayed [10 - 12], which have been widely used in the field of thermal error compensation. Miao *et al* proposed a modeling method of principal component regression (PCR) algorithm [13], which

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can eliminate the influence of multi-collinearity among temperature variables. On this basis, according to the characteristic of PCR algorithm, traverse optimization method for selecting the optimum temperature measuring points is put forward as well. The results show that, PCR model significantly reduces the effects of changes in temperature sensitive points on model's accuracy. Zhang *et al*. proposed a new thermal error model based upon sliced inverse regression (SIR) [14], which can effectively reduce the dimension of input variables without sacrificing variable information. Through the method, the number of temperature sensors was reduced from 29 to 5. The SIR model provides a good prediction accuracy and robustness.

However, compared with various intelligent algorithms, regression modeling method has disadvantages of lower prediction accuracy and poorer robustness. And the temperature variable is still too much; the model based on regression is not efficient. In order to solve the problem, in the paper, according to the calculation results of partial-F statistic, new variable is selected into the regression model one by one, old variables with unapparent effect are deleted, which can reduce the numbers of temperature measurement points, optimize thermal error model, and improve the model prediction accuracy and robustness.

2. TEMPERATURE OF MACHINE TOOL AND THERMAL ERROR MEASUREMENT

In order to analyze thermal error of NC machine tools, optimize temperature measurement points, and determine temperature variables of thermal error model, the experiment of temperature and thermal error measurement was carried out on a NC machine tool, as shown in Fig. (**1**).

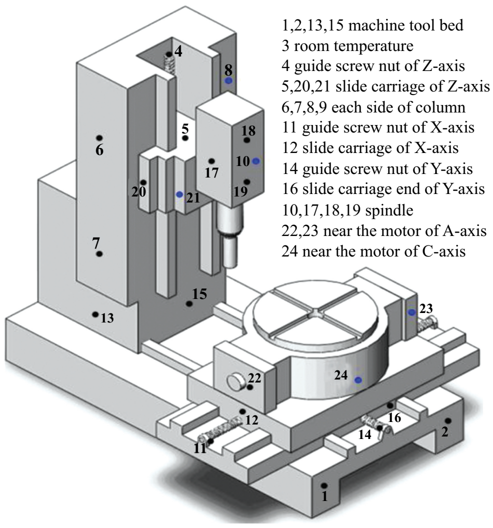

Fig. (1). Main thermal sources of a CNC machine tool.

Through long time observation in machining process of the NC machine tool, the main heat source which had a great impact on thermal error was determined. Temperature sensors were arranged in the main heat source location as shown in Fig. (**1**), which measured the temperature variation of different heat sources. The temperature variation of No.3, No.11 and No.14 heat source is shown in Fig. (**2**).

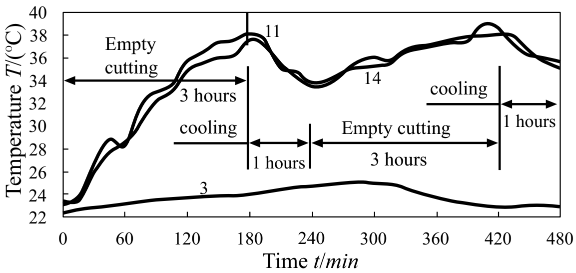

Fig. (2). Temperature variation of thermal sources.

At the beginning of processing, because the temperature of machine tool increased gradually, the temperature of heat source was on the rise. During processing, the temperature of heat source started to fall. In the late phase of processing, the temperature of heat source changed slightly because machine tool had basically reached thermal balance. Hence, it shows that the temperature variation of heat source is basically consistent with machine processing.

In order to measure thermal error of the machine tool, displacement sensors were installed on the worktable of machine tool, and measuring stick was installed at the front of the spindle. Through monitoring the displacement variation of displacement sensor relative to the measuring stick in real time, thermal error of the machine tool in X-axis direction was measured, as shown in Fig. (**3**). From the measurement result as shown in Fig. (**4**), it shows that thermal error change trend of the machine tool is almost same as temperature variation of the heat source. Therefore, temperature variation of the heat source affects thermal error of the machine tool significantly.

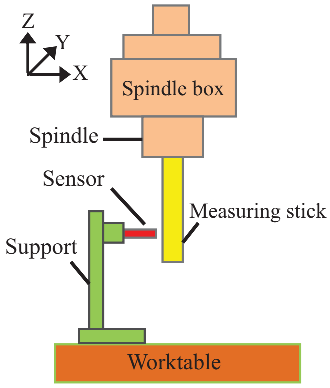

Fig. (3). Measurement of X-axis thermal errors.

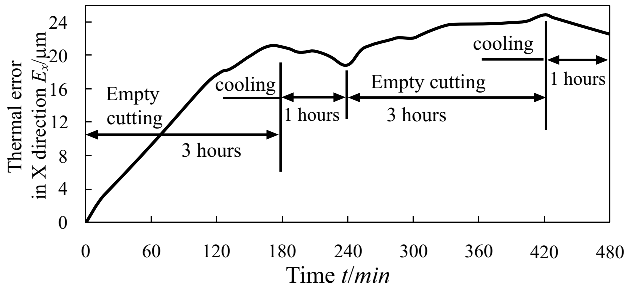

Fig. (4). Thermal errors in X-axis direction.

3. TEMPERATURE MEASUREMENT OPTIMIZATION AND THERMAL ERROR MODELING

With thermal error prediction of the machine tool in real time, thermal error compensation is the main approach to improve the machining accuracy. In order to predict thermal error in real time, it needs to establish the function mapping between main heat source and thermal error of the machine tool, *i.e.* thermal error model. In the experiment, there were 24 main heat sources on the machine tool, which all affect thermal error. If these heat sources are used as temperature variables, different variables will interfere with each other, and the model will be extremely complex, which may affect thermal error real-time prediction. In order to solve the problem, based on stepwise regression, through optimizing the temperature measurement point, and the optimized temperature measurement point being used as temperature variables, the optimal thermal error model was presented.

3.1. Basic Idea of Stepwise Regression

Based on the preliminary combination of variables, through checking out partial-F statistic, new variable is selected into the regression model one by one. When new variable is selected, the old variable which has been selected into the regression model will be checked out again, and unapparent variables are deleted. This process will be going on, until new variable cannot be selected, and unapparent variables cannot be deleted. This is the basic idea of stepwise regression.

Assume the number of nonselected variables is, the number of selected variables is, and denotes the set of selected variables. When the variable which is not selected into the model in A, partial-F statistic can be calculated as follows:

$$F = \frac{SSE(A) - SSE(A, x_k)}{SSE(A, x_k)/(n-l)} = \frac{SSR(x_k|A)}{MSE(A, x_k)} \tag{1}$$

Where, *SSE* denotes sum of squares for error, *SSR* denotes sum of squares for regression, and *MSE* denotes mean square error.

3.2. Thermal Error Modeling Process Based on Stepwise Regression

According to the accuracy request of thermal error model, two critical values of partial-F statistic are determined. Where, denotes the critical value for selecting argument, and takes 100, F_D denotes the critical value for rejecting argument, and takes 50. The specific modeling process is as follows:

(1) The temperatures T_i of 24 main heat sources are regarded as model variables, and simple linear regression model is fitted for each temperature T_i ($1 \le i \le 24$):

$$y = \beta_0 + \beta_i T_i + \varepsilon \tag{2}$$

Where, y denotes thermal error of machine tool, β_0, β_i denotes unknown parameter, and εdenotes unpredictable random error.

Since the gather in type 1 is empty in the beginning of optimizing variable, so,

$$\begin{cases} SSE(A) = SST \\ SSR(T_i|A) = SSR(T_i) \\ MSE(A, T_i) = MSE(T_i) \end{cases} \tag{3}$$

Where, *SST* denotes sum of squares of deviations.

Regression model fitted by single temperature variable carried out partial-F statistic calculation as follows:

$$F_i^{(1)} = \frac{SSR(T_i)}{MSE(T_i)}, \quad i = 1, 2, \cdots, 24 \tag{4}$$

If, $F_{i_1}^{(1)} = \max_{1 \le i_1 \le 24}\{F_i^{(1)}\} > 100$ the regression model which includes independent variable T_{i_1} will be selected as the current model, else the optimization process will stop. It means all temperature variables seldom affect thermal error.

(2) Based on the current model, the other 23 temperature variables are selected one by one, and 23 binary regression models are established. Then, they carried out partial-F statistic calculation as follows:

$$F_i^{(2)} = \frac{SSR(T_i|T_{i_1})}{MSE(T_{i_1}, T_i)}, \quad i \ne i_1 \tag{5}$$

Similarly, if, $F_{i_2}^{(2)} = \max_{i \ne i_1}\{F_i^{(2)}\} > 100$ temperature variable T_{i2} will be selected into the model to obtain a new binary regression model:

$$y = \beta_0 + \beta_{i_1} T_{i_1} + \beta_{i_2} T_{i_2} + \varepsilon \tag{6}$$

On this basis, variable will be checked out whether it still affect thermal error model significantly after T_{i_2} is selected into thermal error model. So it carried out partial-F statistic calculation as follows:

$$F_{i_1}^{(2)} = \frac{SSR(T_{i_1}|T_{i_2})}{\mathrm{MSE}(T_{i_1}, T_{i_2})} \tag{7}$$

If $F^{(2)}{}_{i1} \le 50$, variable T_{i1} will be deleted from model, only variable is retained, else the new binary regression model will be still used for calculation.

(3) Similarly, based on above-mentioned determinate thermal error model, the rest of temperature variables will be selected one by one to fit new regression models. They carried out partial-F statistic calculation. On comparing the results with F_E and F_D, the new temperature variable is decided to be selected or deleted.

The abovementioned steps will be repeated, until the new temperature variable cannot be selected into the model, and the old temperature variable cannot be deleted from the model. Then, the optimization process can be stopped. Finally, determinate thermal error model is the optimal regression model, and the temperature variable of that is the optimal temperature measurement point. In the test, with the above thermal error model based on stepwise regression, thermal error model of a NC machine tool was obtained as follows:

$$\begin{aligned} y &= 8.091 + 20.521T_3 - 11.396T_9 \\ &-4.275T_{11} + 6.301T_{18} - 5.339T_{23} \end{aligned} \quad \textbf{(8)}$$

By the above thermal error model, it can be determined that the heat sources 3, 9, 11, 18 and 23 have a significant effect on thermal error of the machine tool. Through the above optimization process, the number of temperature variables was reduced from 24 to 5, which made measurement workload less, simplified thermal error model, and improved computational efficiency.

4. PREDICTION PERFORMANCE OF THERMAL ERROR MODEL

In order to verify the prediction accuracy of stepwise regression model, model test system was developed, as shown in Fig. (**5**). In the test, temperature signal of main heat source was measured with temperature sensors, and thermal error signal was measured with displacement sensors. Then measurement signal was processed with a DSP system, and computer software was developed to monitor the whole test system. In order to test the prediction accuracy, thermal error model based on stepwise regression was imported into the DSP system. Through measuring the optimized temperature points, five temperature signals were predicted with the model, which could output thermal error value in real time. In the same time, thermal error of machine tool was measured synchronously with displacement sensors. On comparing the measurement result and the prediction result, the prediction performance of the model can be verified.

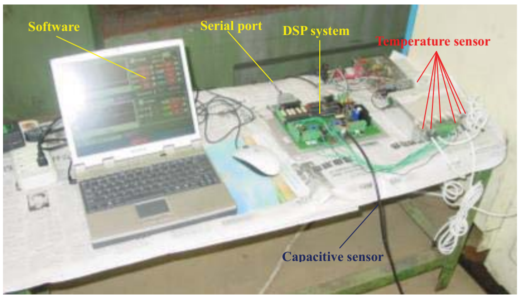

Fig. (5). Test system of thermal error model.

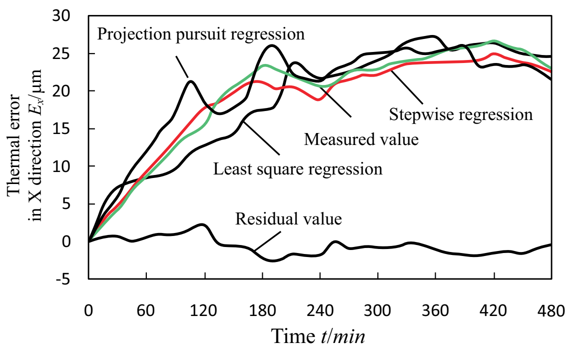

Fig. (6). Prediction performance of different models.

As shown in Fig. (**6**), the prediction accuracy of modeling method based on stepwise regression is obviously better than that of least square regression and projection pursuit regression. Model residual will be less than 5μm after compensation, which satisfies the accuracy request of thermal error model. Meanwhile, due to the method of selecting and deleting temperature variables, thermal error model based on stepwise regression could adjust the model parameters timely for different types of machine tool, and the robustness of that will be considerably improved.

CONCLUSION

A method of temperature measurement point optimization and thermal error model of machine tool based on stepwise regression was proposed, which could reduce the temperature points number of a machine tool from 24 to 5, and avoided the phenomenon of mutual interference occurred in different temperature variables. It simplified thermal error model, while saving calculation time, improving computational efficiency, and prediction accuracy and robustness of the regression model provided the important guarantee for thermal error compensation and improved machining accuracy of machine tool.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not applicable.

CONSENT FOR PUBLICATION

Not applicable.

CONFLICT OF INTEREST

The authors declare no conflict of interest, financial or otherwise.

ACKNOWLEDGEMENTS

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