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Thermal Error Modeling for CNC Machine Tools Based on Parallel LocallyWeighted Linear Regression

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***Abstract*— To abbreviate the displaying season of warm blunders in mass information, an equal privately weighted direct relapse model is proposed based on privately weighted straight relapse and distributed computing stage. The monstrous information is partitioned into different information sub-blocks and the information of each sub-block is examined and handled by the cloud stage at the same time, trailed by the converging of results. Tests are done on a CNC gear crushing machine, the aftereffects of which show that the proposed strategy performs demonstrating based on mass information in a brief timeframe. Likewise, the model appreciates high accuracy and solid strength. This strategy gives reference to the utilization of huge information in warm blunder forecast of CNC machine instruments.**

Keywords-CNC; thermal error; big data; cloud computing; linear regression

I. INTRODUCTION

During the precision machining of machine tools, thermal errors account for 40-70% of all manufacturing errors. Therefore, it is urgent to overcome the impact of thermal errors on the machining precision of machine tools [1].

Currently, the most economical means of reducing the impact of thermal errors is error compensation [2]. Error compensation creates error prediction models on the basis of temperature data of thermal key points and modifies coordinates in CNC program with the predicted values, thereby correcting thermal errors. Common modeling methods, which include neural network [3, 4], support vector machine [5, 6] and multiple linear regression [7, 8], tend to obtain a small amount of sample data through experiments and establish thermal error prediction models on this basis. Due to the limited data samples, the models established are usually characterized by poor prediction robustness. If the massive machining data generated in the process of machine tool machining can be used for modeling, both robustness and precision of the models shall be significantly improved. The existing prediction algorithms have failed to meet the requirements of prediction velocity and prediction precision. For example, traditional multiple linear regression prediction has the advantages of fast training speed and low prediction error rate when used for small data prediction. However, the amount of computation is large when the data amount is huge, costing several hours or several days. Therefore, it is particularly important to solve the prediction problem of mass data.

Based on the actual production data of CNC machine tools, this paper combines locally weighted linear regression prediction algorithm with MapReduce (a cloud computing model) to study thermal error prediction methods. It divides the massive data into multiple data sub-blocks, introduces the cloud platform to analyze and process data of each sub-block simultaneously, and eventually merges the results, which reduces the time overhead for big data processing.

II. LOCALLY WEIGHTED LINEAR REGRESSION MODEL BASED ON CLOUD COMPUTING

A. *Locally Weighted Linear Regression Model*

Locally weighted linear regression model fits polynomial regression curves on the basis of local data and observes laws and trends of local data. The most commonly used method for determining nearest neighbor points is the k-nearest neighbor algorithm [9]. K-nearest neighbor algorithm calculates distances between the prediction point and all data points in the feature space, thereby finding the k points closest to the prediction point.

Supposing that each instance is described by $X=\{s_1, s_2, \ldots, s_n\}$, the distance between two instances X1 and X2 can be obtained through Formula (1):

$$d(X_1, X_2) = \sqrt{\sum_{i=1}^{n}(s_i - s_j)^2} \tag{1}$$

The regression formula is established as follows:

$$\hat{f}(x) = \omega_0 + \omega_1 a_1(x) + \omega_2 a_2(x) + \cdots + \omega_n a_n(x) \tag{2}$$

In the formula, ω_i represents weight calculated according to Formula (1). Its calculation formula is as follows:

$$\omega_i = \frac{1}{d(x_q, x_i)} \tag{3}$$

In the formula, x_q is the prediction point; x_i is a neighbor point of x_q; the weight ω_i is the reciprocal of the distance between x_q and x_i.

In Formula (2), ω_0 is the regression constant; ω_1, ω_2, $\cdots$ and ω_n are regression coefficients; $\hat{f}(x)$ is the regression prediction value; α_i (x) is the i^th attribute value of the instance x. When fitting the above linear functions to a given training set, gradient descent is usually adopted to find coefficients that minimize the errors. In other words, the following equation holds:

$$E(x) = \frac{1}{2} \sum_{x \in nearest} (f(x) - \hat{f}(x))^2 \quad (4)$$

By satisfying the error criteria to achieve local approximation, a gradient descent training rule is obtained:

$$\Delta\omega_j = \eta \sum_{x \in k-Nearesr\ neighbour} K(d(x_q, x))(f(x) - \hat{f}(x))a_j(x) \quad (5)$$

In the formula, η is the learning rate.

B. Implementation of Locally Weighted Linear Regression Algorithm Based on Cloud Computing

1) System Structure

According to Section 2.1, traditional locally weighted linear regression algorithm is seriously defective: when the data to be returned increases, a large amount of computation is required to determine neighbor data points from the massive data. Based on cloud computing, this paper combines locally weighted linear regression algorithm with MapReduce model to achieve parallel prediction of thermal errors.

MapReduce is a parallel programming model and computing framework that handles massive data and follows the divide and conquer philosophy. Therefore, parallel locally weighted linear regression model in this paper involves three phases: map phase, merge phase and reduce phase. In addition, the data of each phase is exchanged in the form of <key, value>. The system framework is shown in Figure 1.

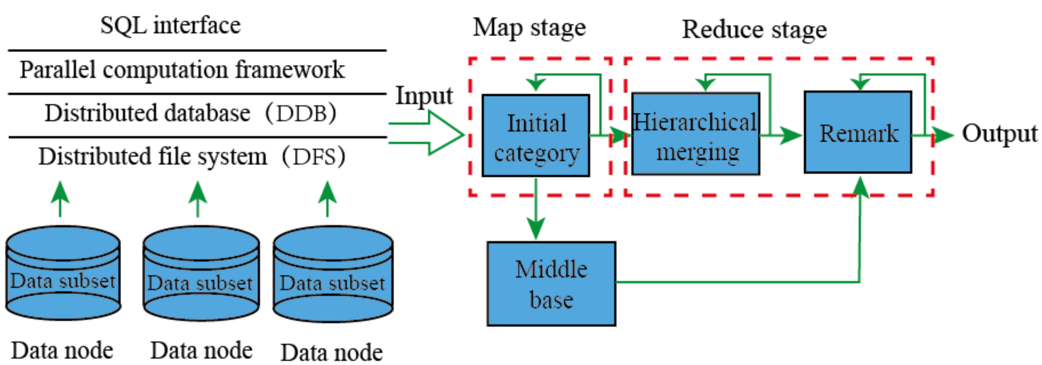

Figure 1. Framework of the Parallel Locally Weighted Linear Regression

a) Map phase

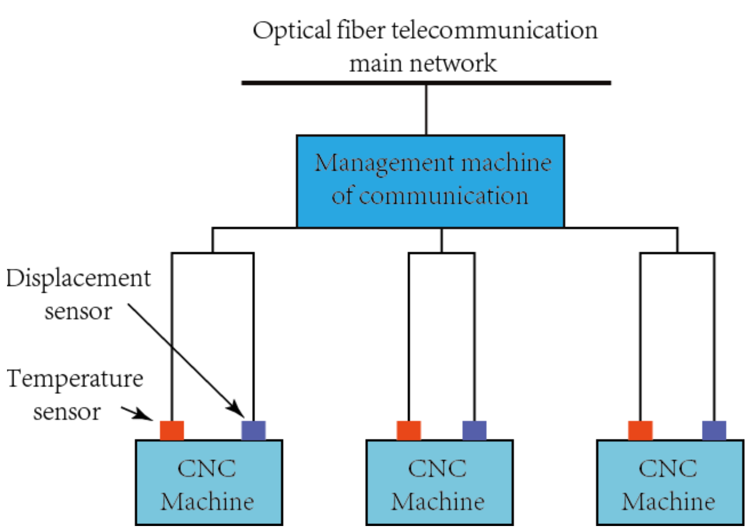

Figure 2. Sketch Map of Data Collection Network

The input data set is divided into multiple data subsets and the data is represented by <key, value>. Wherein, "key" represents the relative offset of current data and "value" represents coordinates of current data in the various dimensions. Based on the local minimum distance algorithm, distances between the test point and the k nearest centers of data subsets are calculated and the computing intermediate results are stored in the intermediate library.

b) Merge phase

The merge phase is designed to merge processed data at the local level. It reorders the sets of intermediate key-value pairs to produce a new two-tuple set and classifies the same key values into the same category.

c) Reduce phase

The reduce function identifies the number of samples and the accumulated coordinate values of corresponding nodes, calculates the k nearest points in each data subset and computes weighted value of each attribute by virtue of the Gaussian mixture model. The results shall be updated into the distributed file system and move to the next iteration until the algorithm converges.

2) Data Collection Framework

The data collection network collects data through sensors placed on machine tools, concentrates data to the collection points by virtue of industrial bus and connects to different communication networks. The collection process is shown in Figure 2.

3) Locally Weighted Linear Regression Prediction Based on Cloud Computing

Firstly, locally weighted linear regression algorithm solves the number of Map. It reads parameter information (data source, data structure, parallelism, incremental field and exception handling method) and divides and adjusts data sets in accordance with current maximum value of incremental field, thereby determining the number of Map. Secondly, k-nearest neighbor algorithm is employed to select k points nearest to the prediction point from each data block processed by Map. Finally, distances between the prediction point and the k nearest points in each Map are compared to screen out the k nearest points and Gaussian mixture model is adopted for weight calculation and parameter determination, thereby completing modeling tasks.

III. Experimental Verification

A. Experimental System

This paper selects YKZ7230 CNC gear grinding machine as the experimental platform, E-type MG-24E-GW1-ANP (temperature sensor manufactured by Anritsu Meter) as the temperature sensor and DGC-8ZG/D (non-contact displacement sensor manufactured by Zhongyuan Measuring) as the displacement sensor. The experimental system is shown in Figure 3.

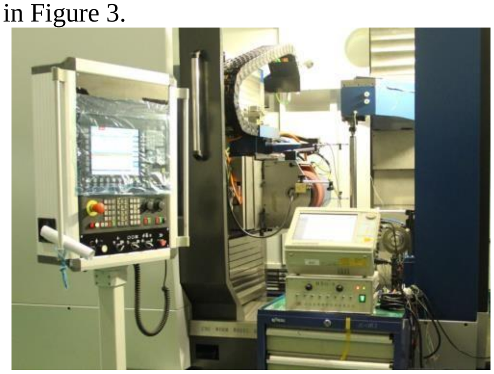

Figure 3. Experimental System

B. Experimental Data

In accordance with the international standard Test Code for Machine Tools - Part 3: Determination of Thermal Effects (IS0 230-3:2001 IDT) [10], all machine tool experiments were carried out under spindle idling. The machine tools operated for 8 hours every day. They were heated for 1 hour and then cooled for 1 hour and the process was repeated for 20 days, during which temperature and thermal error were collected every 3 minutes. Data of the first 10 days was regarded as the training data (see Table I) and that of the last 10 days was deemed as the verification data (see Table II).

TABLE I. Training Data

Date	Hour	Minutes	T1/℃	T2/℃	T3/℃	T4/℃	S1(μm)
1	0	3	22	25	23	23	3
2	0	6	23	27	24	25	5
3	0	9	25	33	27	29	9
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
10	8	60	36	53	49	48	62

TABLE II. Verification Data

Date	Hour	Minutes	T1/℃	T2/℃	T3/℃	T4/℃	S1(μm)
1	0	3	21	23	21	22	2
2	0	6	22	25	23	24	4
3	0	9	24	32	27	28	8
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
10	8	60	34	50	47	45	60

C. Experimental Results

1) Contrast between Locally Weighted Linear Regression Algorithm Based on Cloud Computing and Traditional Linear Regression Algorithm

As Figure 4 shows, the consumed time differs slightly when the sample size is small and the parallel locally weighted linear regression algorithm is superior when the sample size is large, which is attributed to the following reasons: parallel locally weighted linear regression algorithm divides data sets into multiple subsets when the sample size is small, leading to the increase in communication costs and influencing the prediction velocity. However, the parallel algorithm consumes much less time than the traditional algorithm when the iterative time consumed increases.

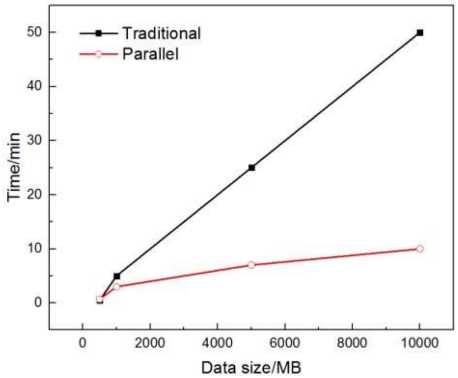

Figure 4. Consumed Time Contrast between the Traditional Algorithm and the Parallel Algorithm

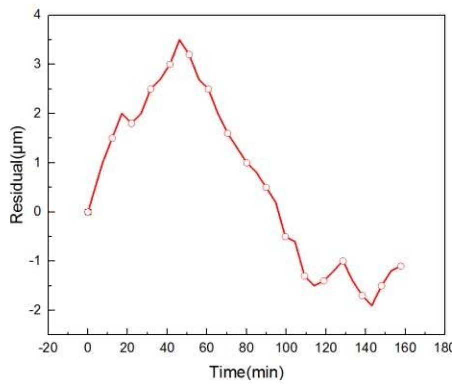

Figure 5. Prediction Result of the Parallel Algorithm

2) Prediction Precision

Prediction results of the locally weighted linear regression algorithm based on cloud computing are demonstrated in Figure 5. According to the figure, the method proposed effectively tracks the actual curve.

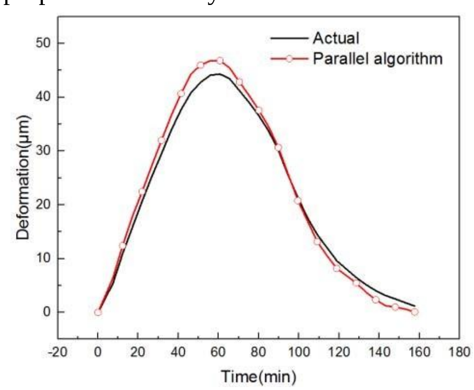

Figure 6. Residual of the Parallel Algorithm

It is revealed in Figure 6 that the maximum residual is 3.5μm and the root-mean-square error is 1.79μm. The prediction results meet the error prediction criteria, which demonstrates feasibility of the method proposed.

IV. CONCLUSION

Experiments are carried out on a CNC gear grinding machine, the results of which show that the method proposed effectively predicts thermal errors generated by the CNC gear grinding machine and enjoys high prediction precision and strong robustness. In addition, the proposed method solves the robustness problem caused by sample insufficiency during small sample data modeling and shortens the modeling time of large sample data.

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