The Thermal Error Modeling with Deep Transfer Learning

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Abstract. Thermal error of CNC machine tools is one of the main factors affecting the machining accuracy. The data-driven method for thermal error modeling is an effective and efficient, but they have some flaws, such as poor accuracy, bad robustness, and etc. because of having no quite enough data set and imbalanced data set. In this paper, a new method based on transfer learning for thermal error modeling is presented for solving the issue of imbalanced data set. The dataset of monitoring the temperature field of the machine tools includes monitoring data of three kinds of operating conditions, namely stopping, idling, and machining. When the fewer idling data is used to train a model, the larger stopping data are introduced as train aids. Transfer learning is adopted to fully learn the common characteristics of the two different working conditions, which can effectively solve the problem of imbalanced dataset. The experimental results prove that our method have better performance than other methods trained only with limited idling data.

1. Introduction

The continuous development of manufacturing industry has put forward higher requirements for the accuracy of CNC machine tools.[1]. Thermal error is the most important factor affecting the accuracy of the machine tool, accounting for 60% of the total error [2].

Compared with the method of reducing thermal error from the design stage [3], the thermal error compensation method is more cost-effective. Accurate thermal error prediction model determines the effectiveness of thermal error compensation. Data-driven thermal error modeling aims to build a model that takes temperature data as input and thermal error as output. Machine learning and deep learning have been widely applied to data-driven thermal error modeling. Early data-driven thermal error modeling mainly used the least squares method [4] and regression analysis [5]. Multiple linear regression model and artificial neural network model [6] are the commonly used models. On this basis, some researchers use genetic algorithm to optimize the model to improve prediction accuracy and robustness [7-9]. However, the data-driven thermal error model do not perform well due to having no quite enough dataset and imbalanced dataset. The dataset of monitoring the temperature field of the machine tools includes monitoring data of three kinds of operating conditions, namely stopping, idling, and machining. Limited by the number of experiments and measurement methods, it is difficult to obtain abundant training data in the idling and stopping state while it is relatively easy to acquire adequate data in the stopping state. The amount of data we obtained under the three operating conditions is quite different.

With transfer learning, knowledge acquired from source domain might be retained and reused in a new target domain [10, 11]. Deep transfer learning (DTL) is a combination of transfer learning and deep
learning. The DTL strategy has been applied in image classification, fault diagnosis, medical image recognition and other areas [12, 13].

In order to address the problem of imbalanced dataset, a new DTL method for thermal error modeling is presented, which can solve the issue of imbalanced dataset and performs well on test data. Transfer learning is used to learn the common characteristics of the data in stopping condition and idling condition while training, which improves the performance of the model and effectively address the issue of imbalanced dataset. In the rest of this paper, the experiment and data source are introduced in Section 2. The thermal error modelling method using transfer learning is presented in Section 3. The thermal error experiments are conducted in Section 4. And the conclusions are draw in Section 5.

2. Experimental setup
The proposed DTL method is verified on a ZK5540A CNC machine tool. The structure of the ZK5540A CNC machine tool is shown in figure 1.

![Figure 1. The structure of ZK5540A CNC machine tool.](image)

Fiber Bragg Grating (FBG) temperature sensors are applied to monitor the temperature field of ZK5540A. There are 124 temperature sensors placed on various locations of ZK5540A and 4 temperature sensors placed around the ZK5540A. Table 1 shows the arrangement of the temperature sensors at each position.

| Points   | Positions | Number of Points |
|----------|-----------|------------------|
| T1-T52   | Spindle   | 52               |
| T53-T60  | Beam      | 8                |
| T61-T92  | Column    | 32               |
| T93-T124 | Guide rail| 32               |
| T125-T128| Environment| 4               |

The cutting tool of ZK5540A is replaced with a test rod and laser displacement sensors (DIS sensors) are placed to measure the displacement in different directions. It is hard to monitor the thermal error data under the machining condition, therefore, we only monitor the thermal error data under stopping and idling condition.

There are two experimental conditions in our experiments: measurement in downtime and measurement during spindle rotation at different constant speeds. Continuous measurement for 24 hours in the state of downtime and 500, 1000, 1500, 2000 r/min separately for a continuous 5h in the state of spindle rotation at constant speeds. Collect data every 5s, which means 17280 samples are collected in stopping state and 3600 samples are collected in every rotation experiment. This indirectly simulates the imbalance of data under different working conditions. Samples in rotation experiment are used for model validation. Both temperature and thermal errors change slowly, therefore in model validation, the collected data can be down sample to 360 samples. Research shows that the thermal error during machine tool operation is mainly the Z axial thermal error [14]. Therefore, the thermal error of Z axial is the main research object of thermal error modelling.
3. Deep transfer learning method for thermal error modeling

As shown in figure 2, the DTL method is composed of thermal error prediction module and domain adaptation module, which is modified from [13]. The two modules share the output of feature extractor. The convolution layer in feature extractor can automatically learn the data features. Based on the extracted features, it performs regression fitting on the thermal error. The domain adaptation module connects the features extracted by the convolutional layer to learn the domain-invariant features.

![Figure 2. Structure illustration of DTL method.](image)

3.1. Thermal error prediction

As shown in figure 3, thermal error prediction module can be viewed as a simple CNN model, which includes input layer, feature extractor, fully connected layer, and output layer. And figure 2 shows the details of feature extractor.

![Figure 3. The structure of thermal error prediction.](image)

The input is target domain data. After the convolution and pooling operations, the input temperature measurement point information is mapped to the features output by the pool1 layer. The output of feature extractor is flattened by FC1, and the output of FC2 is the predicted thermal error. Define mean square error as prediction loss function:

$$L_p = \frac{1}{N} \sum_{n=1}^{N} (y_n - \hat{y}_n)^2$$

(1)

$N$ is number of the training samples, $y_n$ is the ground truth of thermal error, $\hat{y}_n$ denotes the predicted value of the corresponding thermal error.

3.2. Domain adaptation
Domain adaptation module is to learn the domain-invariant features, it has two core sub-modules, domain adversarial module and MMD metric module. Figure 4 shows the structure of domain adaptation.

**Figure 4.** The structure of domain adaptation.

The domain adversarial sub-module can be viewed as a classifier. The output of feature extractor is reversed by gradient and then fed into the full connection layer. The output layer $D_O$ can be regarded as a logistic regression classifier.

The goal of general classifiers is to separate different categories as much as possible. Different from general classifiers, the goal of domain adversarial sub-module is not to separate the two categories as much as possible in the training process in order to learn common features of two domains. Domain classification loss can be defined as [13]:

$$L_D = \frac{1}{N} \sum_{i=1}^{N} \left( y_i \log d(x_i) + (1 - y_i) \log \left(1 - d(x_i)\right) \right)$$  \hspace{1cm} (2)

$y_i$ is the true domain label of $i$th sample, and $d(x_i)$ is the predicted domain label for $i$th sample. Domain label is to distinguish between the source domain and the target domain.

The discrepancy of two domains is estimated by MMD metric, which is based on the corresponding RKHS distance [15]. The formula of MMD is as follows:

$$D = MMD(X_s, X_t) = \left\| \frac{1}{N_s} \sum_{i=1}^{N_s} \varphi(x_i^s) - \frac{1}{N_t} \sum_{j=1}^{N_t} \varphi(x_j^t) \right\|_H$$  \hspace{1cm} (3)

$N_s$ and $N_t$ are the sample number of source domain and target domain, and $\varphi(\cdot)$ represents the function of feature extractor and full connection layer.

The cost function of the proposed method is presented as follows:

$$L = L_p - \lambda L_D + \mu D$$  \hspace{1cm} (4)

During the training process, $\lambda$ change from 1 to 0, $\mu$ change from $10^{-3}$ to $10^{-5}$. And the adaptive moment estimation (Adam) algorithm is used to minimize the cost function.

4. Results and discussion

Mean square error and prediction accuracy can be used as a measure of the performance of the model. The residual value is the error between the ground truth value and the fitting value, which can be used to examine the rationality of the model assumptions and the reliability of the data.

In our experiment, we define the data measured in the stopping condition as the source domain data, and the target domain data is obtained by the spindle rotating at a constant speed.

In order to verify the proposed methods, we have also implemented three methods that do not adopt transfer learning strategies to compare with our method. The four model are tested on the data of the machine tool under 500r/min and 2000r/min. Table 2 shows the results of different speeds in four models, figure 5 and figure 6 show the comparison of different speeds in four models.
Table 2. The result of different speeds in four models

| Model | Speed    | $|e_i|_{max}/\mu m$ | MSE          | Prediction accuracy |
|-------|----------|--------------------|--------------|--------------------|
| MRA   | 500r/min | 19                 | $7.6 \times 10^{-5}$ | 86.29%             |
| MRA   | 2000r/min| 18                 | $8.7 \times 10^{-5}$ | 87.69%             |
| BP    | 500r/min | 16                 | $7.1 \times 10^{-6}$ | 91.37%             |
| BP    | 2000r/min| 16                 | $6.4 \times 10^{-6}$ | 92.07%             |
| CNN   | 500r/min | 12                 | $5.7 \times 10^{-6}$ | 94.02%             |
| CNN   | 2000r/min| 12                 | $6.0 \times 10^{-6}$ | 95.13%             |
| DTL   | 500r/min | 11                 | $6.1 \times 10^{-6}$ | 94.87%             |
| DTL   | 2000r/min| 10                 | $5.8 \times 10^{-6}$ | 95.91%             |

Figure 5. Comparison of different models in 500r/min.
Figure 6. Comparison of different models in 2000r/min.

Table 2 shows that the extremum of residual errors of DTL model is 10μm, while the extremum of residual errors of other models is about 18μm. The prediction accuracy of the DTL model is maintained at about 95% and the MSE value of DTL model is maintained about $5.8 \times 10^{-6}$, the performance of which is slightly better than the CNN model, much better than MRA and BP model. Figures 5 and 6 show the ground truth value curve and the prediction curves of each model at different speed, it can be seen that the prediction curves of MRA and BP are far from the ground truth values, while the prediction curves of CNN and DTL models are basically consistent with the experimental measurements.

5. Conclusion

In order to address the problem of imbalanced dataset, we have adopted transfer learning strategy that introduces a large number of relevant data when modelling, which can effectively improve the prediction accuracy and robustness of the model. Abundant predictability tests are conducted under idling state, and the performance of the DTL model is better than the other models without transfer learning strategy in terms of accuracy and robustness. Verifications are only carried out when spindle rotation at constant speed. For spindle rotation with different speed spectra and the actual cutting state, it still needs further research.

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