Thermal Deformation Prediction in Machine Tools by Using Transfer Functions

Yu SETO*[1], Fumihiro SUZUMURA*[2] and Gonojo KATAYAMA*[3]

*1 Graduate School of Science and Technology, Hiroshima Institute of Technology
2-1-1 Miyake, Saeki-ku, Hiroshima 731-5193, JAPAN
a310071@cc.it-hiroshima.ac.jp

*2 Department of Mechanical Systems Engineering, Hiroshima Institute of Technology
2-1-1 Miyake, Saeki-ku, Hiroshima 731-5193, JAPAN
f.suzumura.br@it-hiroshima.ac.jp

*3 Professor emeritus, Hiroshima Institute of Technology
2-1-1 Miyake, Saeki-ku, Hiroshima 731-5193, JAPAN
katayama@me.it-hiroshima.ac.jp

Abstract

The purpose of this paper is to estimate the thermal deformation of machine tools. The prediction method of thermal deformation is constructed from transfer functions between specified surface temperatures and the relative displacement in the cutting area. The relative displacement in the cutting area is predicted using some specified surface temperatures near the heat source in machine tools. The parameters of transfer functions are derived by the Steepest Gradient Algorithm. As a result, the prediction method can predict with enough certainty at what rate the temperature changes the most rapidly on a machine's startup transient behavior. The method proposed in this paper is remarkably effective to estimate thermal deformation and confirm that the error between experimental and estimated values will be remarkably reduced. Furthermore, the proposed method is applied to the vertical machining center in order to verify the effectiveness.

Keywords: thermal deformation, prediction, machine tool, transfer function, vertical machining center

1 Introduction

Several kinds of machine tools such as high speed and high performance machine tools, combined multi-function machine tools, and ultra-precision processing machine tools are developed. Manufacturing by using the accuracy of the micrometer order has become possible. Increasingly, changes in the business requirements of manufacturing industries are driving machining systems to be more accurate and more productive. Many automated machining operating solutions are available for higher productivity and machine tools are evolving to have a higher accuracy. However, it is difficult to maintain accuracy when the machine tools and the precision instrument with very high accuracy are operated continuously. The factor that causes the decrease in the processing accuracy includes thermal deformation. Thermal deformation is one of the major error sources of cutting working pieces, which is due to the temperature variation and non-uniform distribution characteristic. It will cause a 40-70% error during the cutting process in the machine tools. Therefore, it is important because of the processing that improves machining accuracy by countermeasure for reducing thermal deformation or improving accuracy with error compensation. It is difficult to keep the machining accuracy under a complex operation of machine tools in the structural heat interception and the cooling of the heat source because thermal deformation greatly influences a rapid temperature.

Several kinds of countermeasure for reducing thermal deformation have been surveyed and reviewed. The transfer functions between the ambient temperature variation and the thermal deformation of the machine tools, as well as a method of estimating the thermal deformation by utilizing the measured transfer functions have been proposed [1]. The basic characteristics of the thermal deformation have been obtained by the experiments and the relative thermal deformation has been estimated using the basic characteristics [2]. An estimation model utilizing transfer functions to identify thermal deformation of machine tools has been developed by utilizing available information in CNC units [3]. A thermal deformation control for aerostatic spindle systems has been proposed considering heat balance in an objective spindle bearing system [4]. An analytical method with a Laplace transformation has been developed for the inverse heat conduction problem [5]. Neural network models have been constructed to estimate thermal deformation by employing time-series data of the measured temperatures [6]. The thermal deformation prediction has been developed by using transfer functions in a machine tool model [7], [8].

The purpose of this paper is to estimate the thermal deformation of machine tools by using transfer functions. The estimation model of the thermal deformation based on the frequency domain is constructed from the transfer functions between specified surface temperatures and the relative thermal displacement in the cutting area. The relative displacement in the cutting area is predicted using two specified surface temperatures near the heat source in the machine tool model. The parameters of the transfer function are derived by the Steepest Gradient Algorithm. Furthermore, in order to predict both surface roughness and accuracy of pieces of work manufactured by vertical machining center, the proposed method is applied and its effectiveness is verified.

2 Prediction method

The thermal deformation prediction method is derived by using the transfer function between the surface temperature variation of the structural parts and the relative thermal displacement in the cutting area. That is, the thermal displacement that originates from the thermal gradient of the structural parts is predicted by Eq. (1).

$$D_i(s) = G_i(s)\Theta_i(s),\ i = 1, 2, \cdots, n \tag{1}$$

Where, $D_i(s)$ is the thermal displacement of the cutting area due to the influence of surface temperature variation $\Theta_i(s)$, and $G_i(s)$ is the transfer function between $D_i(s)$ and $\Theta_i(s)$. The thermal deformation prediction method is derived by overlapping these.

$$D(s) = D_1(s) + D_2(s) + \cdots + D_n(s) \tag{2}$$

The diagram for the thermal deformation prediction is shown in **Fig. 1**. The transfer function $G_i(s)$ is defined,

$$G_i(s) = \frac{K_i(s + T_{i1})}{(s + T_{i2})} \tag{3}$$

where, K_i and T_{ij} ($i = 1, 2, \cdots, n$, $j = 1, 2$) are the parameters to be estimated. The transfer function $G_i(s)$ is described in the time domain by using a delta function.

$$g_i(t) = K_i\delta(t) + K_i(T_{i1} - T_{i2})e^{-T_{i2}t} \tag{4}$$

where, $\delta(t)$ is the Dirac delta function. The Dirac delta function is formally described as follows.

$$\begin{cases} \delta(x) = 0 & (x \neq 0) \\ \delta(x) = \infty & \end{cases} \tag{5}$$

$$\int_{-\infty}^{\infty} \delta(x)dx = 1 \tag{6}$$

The estimated value of the relative thermal displacement by using the thermal deformation prediction method is obtained by

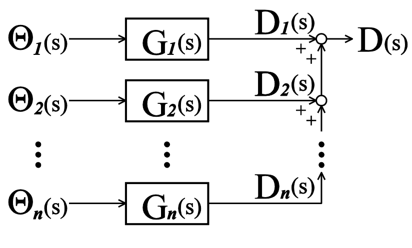

Fig. 1 Diagram for the thermal deformation prediction

$$\bar{d}_i(t) = K_i\theta_i(t) + K_i(T_{i1} - T_{i2})\int_0^t e^{-T_{i2}\tau}\theta_i(t-\tau)d\tau \tag{7}$$

The integrated square prediction errors E over the entire measurement time are obtained by using the estimated value $\bar{d}(t)$ and the relative thermal displacement $d(t)$.

$$E = \int_{-\infty}^{\infty} (\bar{d}(t) - d(t))^2 dt \tag{8}$$

The parameters (K_i , T_{i1} , T_{i2} , $i = 1, 2, \cdots, n$) are determined by using the Steepest Descent Algorithm (SDA) which minimizes the criterion E .

The proposed method is applied to the machine tool model and vertical machining center in order to verify the effectiveness.

3 Prediction results in the machine tool model

It is considered that the relative displacement in the cutting area is able to be predicted by measurement of the surface temperature variation and the thermal gradient related to the thermal capacity of the material. The machine tool model is designed and manufactured based on the outcome of the experiment.

3.1 The machine tool model

The machine tool model is shown in **Fig. 2**. The structural parts of the machine tool model are made of FC300. The cutting area of the machine tool model is assumed to be both tips to be a cutting tool and a work. The heat source is located on the column parts of the assumed cutting tool side and constant heat source is generated and controlled by a temperature controller. The machine tool model deforms due to the influence of this heat source, and the relative thermal displacement in the cutting area changes. The relative thermal displacement is measured by using differential transformers. The surface temperatures at points A and B of the machine tool model shown in **Fig. 2** are measured by using thermoelectric couples. It is thought

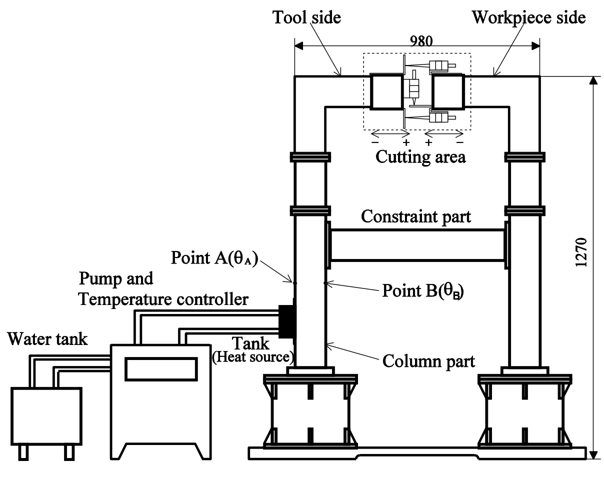

Fig. 2 Machine tool model

that the machining error is measured only in the horizontal direction. The relative thermal displacement assumes the approaching direction to be positive and the opposite direction to be negative.

3.2 Experimental results

An experimental result under the condition which is set at a heat source temperature of 20K and continuously operates on 18ks is shown in **Fig. 3**. The temperature variation of point A and B rapidly increases to about 9.5K and 6.2K respectively during operation from 0s to 12ks, and gradually increases afterwards. The relative thermal displacement rapidly increases to about 2.2ks, and an almost constant value is kept from about 13.2ks after gradual decrement. The maximum relative thermal displacement is 37.9μm at 2.2ks. The relative thermal displacement decreases from 2.2ks while the temperature of point A and B continues to rise. The thermal deformation of the machine tool model is greatly related to the thermal gradient of the structural parts. Therefore, it is thought that relative thermal displacement can be predicted by measuring the surface temperature of two points with high thermal gradients.

3.3 Prediction results

The prediction model in the machine tool model is obtained by displacement and temperatures of point A and B shown in **Fig. 4**. The transfer functions $G_A(s)$ and $G_B(s)$ are defined by

$$G_A(s) = \frac{K_A(s+T_{A1})}{(s+T_{A2})} \tag{9}$$

$$G_B(s) = \frac{K_B(s+T_{B1})}{(s+T_{B2})} \tag{10}$$

where, K_i and T_{ij} ($i = A, B,\quad j = 1, 2$) are the parameters to be estimated by minimizing the integrated

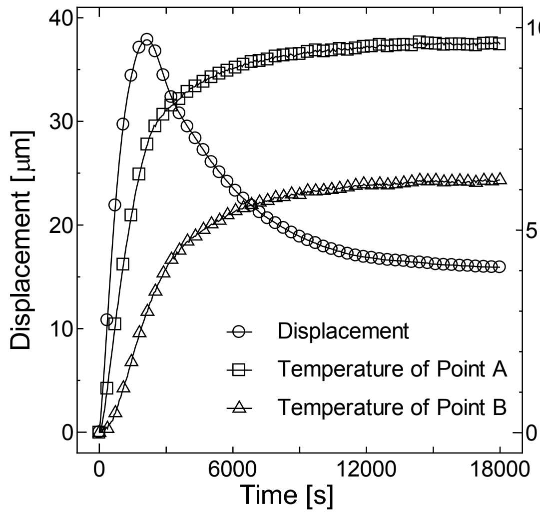

Fig. 3 Experimental result

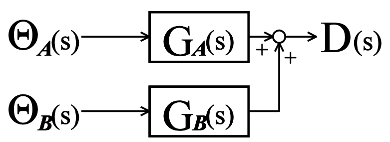

Fig. 4 Prediction model in the machine tool model

square prediction errors over the entire measured time. The predicted result is shown in **Fig. 5**. The estimated value of relative thermal displacement is 37.9μm when the maximum relative displacement is about 2.16ks. At this time, the experimental value is 37.8μm and error is 0.1μm. An excellent prediction result is obtained in spite of the rapid temperature rise because the maximum prediction error is -1.0μm over the entire measured time.

4 Prediction results in vertical MC

The proposed method is to apply machine tools to verify effectiveness. Ordinarily, machine tools compensate for thermal deformation and measuring the cutting area of machine tools during processing is difficult. However, in order to achieve ultra-precision machining technology, it is important to establish a method for minimizing thermal deformation.

4.1 Experimental results in Vertical MC

Ordinary, the vertical machining center compensates for the thermal displacement associated with the spindle running of the machining center. However, it is thought that the influence that occurs in the surface roughness of a piece of work made by the thermal deformation is an object of thermal deformation prediction. First of all, the grooving of some plate materials is formed by using a representative vertical machining center (Okuma, MB-56VA/B). SS400, which has a square 500mm on the side and a thickness of 10mm, is used as the plate material. A spiral grooving shown in **Fig.6** is formed on the plate materials by using the vertical machining center. The groove depth is 0.5mm. The spindle of the machining tool uses superfine cemented carbide as a base metal and is coated with a titanium aluminum nitride compound. The

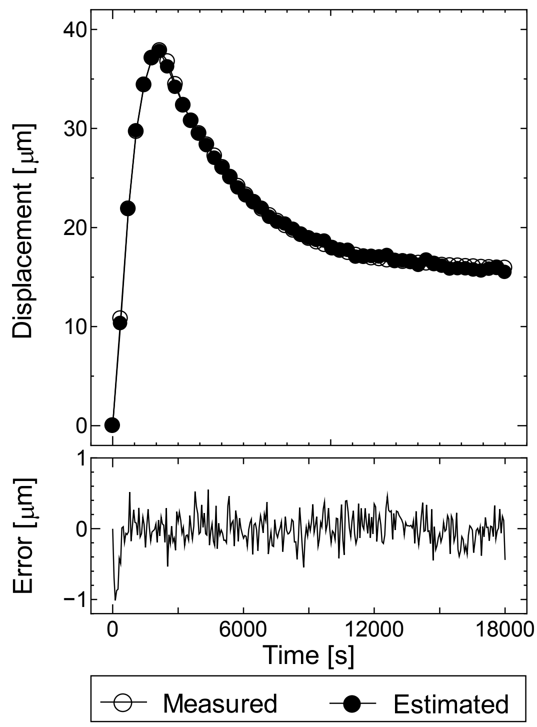

Fig. 5 Prediction result in the machine tool model

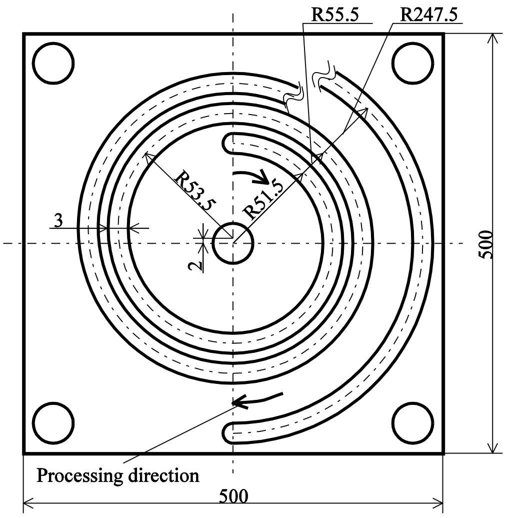

Fig. 6 Spiral grooving

Table 1 Processing conditions

Spindle diameter	ϕ3 mm
Spindle speed	7000 r/min
Forward speed	210 mm/min

processing conditions are shown in **Table 1**.

The surface temperature of the machining center follows the internal temperature and the ambient temperature, but the surface temperature variation is slightly smaller than that of the ambience because of the compensated thermal deformation. Therefore, the surface temperature of the spindle motor exposed for natural air cooling was measured during processing. The processing time was 225min. The surface temperature of spindle motor is shown in **Fig. 7**. The relative surface temperature to ambience of the spindle motor increases exponentially to 20K during processing. Immediately after processing, the surface temperature decreases to 2.5K because of natural air cooling. The surface roughness of the processed material is measured by a stylus type surface roughness measuring instrument (Tokyo Seimitsu, SURFCOM FLEX 130A). The surface roughness is shown in **Fig. 8**.

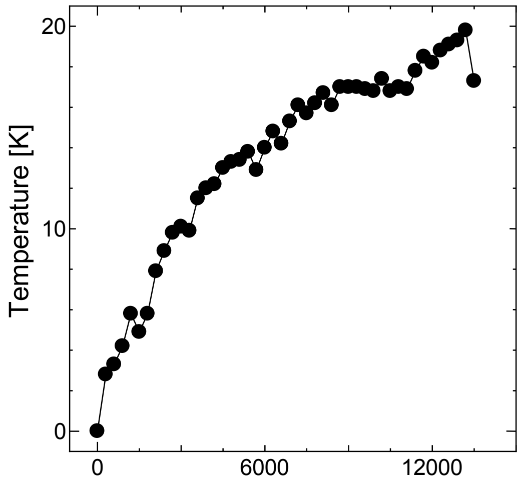

Fig. 7 Measurement temperature

The surface roughness variation decreases exponentially and the maximum range is 1.3μm, which is caused by spindle durability.

4.2 Prediction results in Vertical MC

The prediction model in the vertical machining center which is obtained by the surface roughness and the surface temperature of the spindle motor is shown in **Fig. 9** and the prediction result is shown in **Fig. 10**.

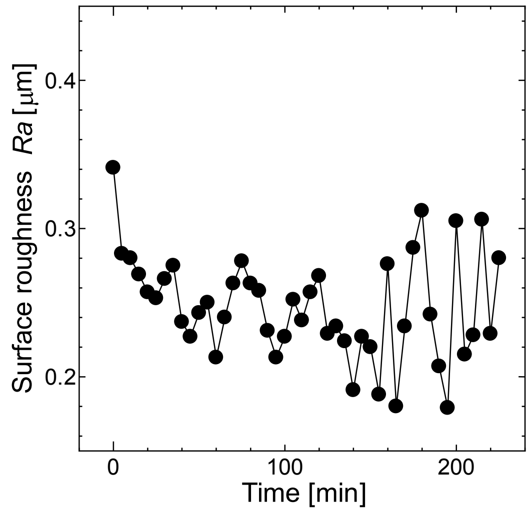

Fig. 8 Surface roughness Ra (Average ± 1.96σ)

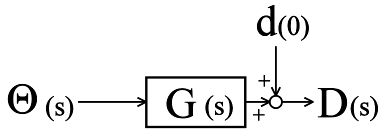

Fig. 9 Prediction model in the vertical MC

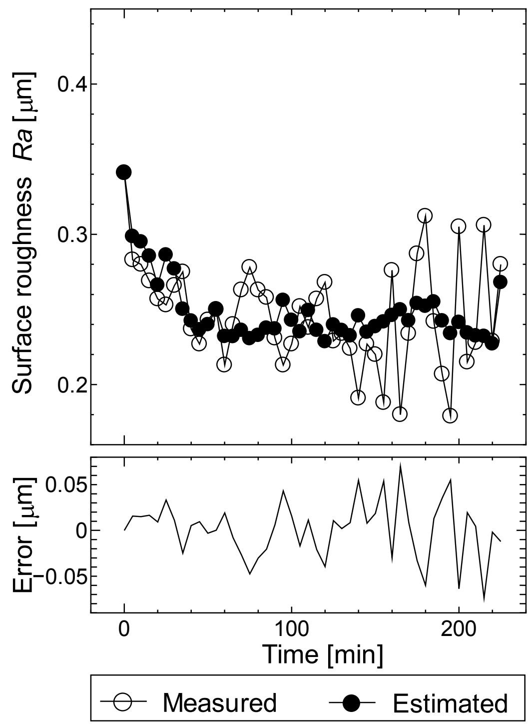

Fig. 10 Prediction result in the vertical MC

The mean squared prediction error of the surface roughness is 0.03μm and the prediction error range is ± 0.07μm over the entire measured time.

5 Conclusions

In this paper, the machine tool model is designed and manufactured, and the thermal deformation prediction in the machine tools is proposed by using transfer functions. Furthermore, the proposed method is applied to the vertical machining center and its effectiveness is verified. As a result, the following conclusions can be drawn.

(1) The thermal deformation prediction proposed by using transfer functions is effective, and it is confirmed that the proposed method only has enough surface thermal gradients.

(2) In the machine tool model, the maximum error of the relative thermal displacement is 0.1μm; therefore, an excellent prediction result can be obtained.

(3) The sum of the measurement error of differential transformers and thermoelectric couples is 2.5μm. The errors for each experimental condition have been within this range.

(4) In the vertical machining center, the surface roughness of the processed material is measured and its prediction result can be obtained from the surface temperature of the spindle motor. The prediction error range in vertical machining is 0.07μm over the entire measured time.

(5) Because some temperature measurement points can be used anywhere, thermal deformation of the machine tools can be estimated without depending on the structure.

In further work, the proposed thermal deformation prediction will be applied to multi-functional combined CNC machine and ultra-precision processing machine tools.

References

[1] Moriwaki, T., Shamoto, E. and Tokunaga, T., "Thermal Deformation of an Ultraprecision Machine Tool due to Environmental Temperature Change", Transaction of Japan Society of Mechanical Engineering, C, Vol.63, No.615, (1997), pp.4025-4030.

[2] Hori, S., Nishiwaki, N., "Study on Thermal Deformation of Machine Tool Structure Estimated by Its Basic Characteristics", Transaction of Japan Society of Mechanical Engineering, C, Vol.64, No.621, (1998), pp.1836-1841.

[3] Shamoto, E., Hino, R., Tomie, T., Matsubara, Y. and Moriwaki, T., "Estimation of Thermal Deformation of Machine Tool by Utilizing Available Information in CNC Unit", Transaction of Japan Society of Mechanical Engineering, C, Vol.69, No.686, (2003), pp.2775-2782.

[4] Yoshikawa, H., Matsumura, S., Hashizume, H. and Shinno, H., "Minimizing Thermal Deformation of Aerostatic Spindle System by Temperature Control of Supply Air", JSME international journal, Series C, Vol.49, No.2, (2006), pp.606-611.

[5]Monde, M., Mitsutake, Y., Siki, T. and Nishimoto, T., "Analytical Approach Solution with Laplace Transformation to the Inverse Problem of One Dimensional Heat Conduction", Transaction of Japan Society of Mechanical Engineering, C, Vol.66, No.642, (2000), pp.519-527.

[6] Chang, C.W., Kang, Y., Chen, Y.W., Chu, M.H. and Wang, Y.P., "Thermal Deformation Prediction in Machine Tools by Using Neural Network, Neural Information Processing", Springer-Verlag Berlin Heidelberg, (2006), pp.850-859.

[7] Suzumura, F., Makihara, H. and Katayama, G., "Thermal Deformation Prediction in Machine Tool Model by Using Transfer Functions" The 2nd International Conference on Design Engineering and Science, (2010), pp,145-150.

[8] Suzumura, F., Makihara, H., Ohtani, K, Ikeda, M., Fukushima, C. and Katayama, G., "Thermal Deformation Prediction in Machine Tool Model by Using Transfer Functions with Time Delay", Advanced Materials Research Vols. 189-193, (2011), pp.4064-4067.

Received on November 30, 2013

Accepted on February 3, 2014