Abstract
In order to perform accurately scheduling of machining using a machine tool, it is necessary to estimate the actual machining time. The machining time is generally estimated by CAM systems. However, the error between the estimated and real cutting times is considerable because the systems do not consider the control and functional characteristics of the machine tool. In addition, control functions are installed in machine tools to achieve high precision and high speed motion while optimizing the tool paths and control parameters. The functions significantly affect the machining time. However, estimating machining time is difficult, thereby complicating optimization process. In this study, a method to identify the control characteristics and actual tool paths and a system to estimate the cutting time were developed. Furthermore, an estimation system using a deep neural network (DNN) was constructed to incorporate a control function. Finally, verification experiments were conducted wherein the estimation accuracy of the machining time was found to be within 5%.

Keywords: NC machine tool, CAM system, Machining time estimation, Control function, Deep neural network

1. Introduction

Accurate estimation of machining time is essential to efficiently schedule machining processes using a machine tool. Currently, although the machining time is estimated using CAM systems, these systems usually calculate the machining time using a simple theory wherein the entire tool path distance is divided by the value of the command feed rate of the NC program. The error between the actual machining time and the estimated machining time is considerable (Maropoulos P.G. et al. 2000). This error occurs because of the following two reasons. The first is that the control characteristics of each machine tool are not considered in estimation by the CAM systems. The second is that the smoothing function for shortcut paths to avoid large acceleration and deceleration is neglected.

Recently, several studies have been conducted on estimating the machining time. Monreal M. and Rodriguez C.A. (2003) and Yan X. el al. (1999) proposed systems that identify the machining time from the actual cutting feed rate considering the acceleration. Siller H. et al. (2006) proposed a method to estimate the machining time using a velocity distribution map of the actual velocity obtained from several test experiments. Altintas Y. and Tulsyan S. (2015) estimated the machining time by deriving the cutting-speed profile during a multi-axis machining process from the jerk, acceleration, and feed rate. However, these methods are not based on the control characteristics of the machine tool, and the accuracy of estimating the machining time remains low. In addition, Saito K. and Aoyama H. (2012) proposed a method for estimating the machining time wherein the sampling time and upper limit of the speed of the machine tool were considered in the analysis. However, the control characteristics are identified manually. The error in measuring the machining time is still considerable, and the operators are heavily burdened. Furthermore, the method cannot cope with
the change in the control characteristics accompanying the improvement in the servo performance in recent years, and the estimation accuracy is low in using latest machine tools.

Furthermore, the latest machine tools have the high accuracy profile machining function to increase the machined surface properties. This function makes re-construction of the tool paths of an NC program commanded by a CAM system and optimization of the feed rate, acceleration, and deceleration for servo control. When machining with the high accuracy profile machining function, a user has to set the three parameters for the function. In addition, the machining time varies significantly because of the differences in the parameters in spite of using the same NC program. The user cannot understand the process and control parameters because the algorithms are not opened. Thus, estimating the machining time based on the control theory and algorithms of machine tools is difficult.

In this paper, two methods to estimate machining time have been proposed; one is the method based on predicting actual tool paths by considering the control characteristics of a machine tool, the other is the method using a deep neural network (DNN) for the case that algorithms determining the tool paths is not opened such as the high accuracy profile machining function. In addition, some machining experiments were performed to confirm the viability of the two proposed methods.

2. Control theory/algorithim of the NC machine tool

The NC controller of an NC machine tool generates interpolation points for each sampling time to control the positioning of the cutting tool when moving between the command points (G01 and G02/G03). The interpolation points are the command positions in each sampling time for each servo system in an NC machine tool. The sampling time is the
minimum unit time required to generate an interpolation. In addition, a machine tool drives linearly between the interpolation points, regardless of the operation type such as G01 and G02/G03. Therefore, interpolation points are generated for each “sampling time \( T \times \text{command feed rate } F \).” However, the distance between the command points is not generally an integral multiple of the “sampling time \( T \times \text{command feed rate } F \).” Hence, as the last interpolation distance is a fraction, the length needs to be adjusted by reducing the distance \( FT \). The sampling time \( T \) is specific and not changeable on an NC controller; thus, the command feed rate \( F \) must be decreased to \( F' \) for the adjustment, as shown in Fig. 1. Although the distance is matched in Fig. 1, high acceleration and deceleration will occur in the last interpolation path. This description is not the exact explanation of the control process but easy to understand it. Because this sudden acceleration/deceleration leads to degradation of the properties of the machined surfaces, a smoothing control is performed in an NC machine tool. In this function, the last interpolation point is put on the next block path with a shortcut function when the last interpolation distance is shorter than the “sampling time \( T \times \text{command feed rate } F \),” as shown in Fig. 2. By employing this control, the interpolation-point distance will be equal to the length \( FT \), and the feed rate can be kept constant.

3. Estimation method of machining time

3.1 Identification of control parameters

The following two control parameters are used to estimate machining time according to analyzing the actual tool paths: the sampling time and in-position check time. Saito (2012) proposed a method to experimentally identify the sampling time by preparing a plurality of tool paths that are made longer by a minute distance for a particular distance and measuring the processing time of each tool path. However, as the machining time of the experiment is measured manually, the error occurring in the measurement of the machining time is high, and the operator is heavily burdened. Hence, in this study, macro programs that measure the machining time in the NC program were incorporated as shown in Fig. 3. The macro programs automatically acquire the time of each motion performed by tool paths with minute distances. Then, the sampling time is accurately identified by the time acquired by the macro programs.

In addition, positioning command (G00) drives in the maximum feed rate in each NC machine tool. In positioning motion, it is confirmed that the positioning is precisely performed or not. The time to confirm the positioning including the acceleration and deceleration time is called in-position check time. The in-position check time can be derived by subtracting the total time of the sampling time required for the tool paths from the real machining time (moving time) required for the paths. However, the acceleration/deceleration time varies depending on the angle formed between a tool path and the subsequent tool path. Therefore, the in-position check time at angles 0°, 60°, 90° and 120° was experimentally obtained and was derived using a quadratic function approximation, as shown in Fig. 4.

\[
y = 2.2\times10^{-2}x^2 - 4.7\times10^0x + 3.1\times10^2
\]
3.2 Tool path prediction

As described previously, in the case of the linear interpolation command (G01) and circular interpolation command (G02/3), when the final interpolation distance of an interpolation command is less than $FT$, the shortcut control is performed to avoid sudden any acceleration/deceleration by a smoothing control. In this study, the tool-paths by the shortcut control are estimated by deriving the coordinates of each interpolation point with $FT$. Figure 5 shows the predicted tool paths in which the distance between interpolation points is $FT$.

In Fig. 5, while moving from the first tool-path point $C_1$ to the second tool-path point $C_2$, the interpolation points $I_1$ and $I_2$ are generated for each distance of $FT$. The coordinates of the interpolation points $I_1$ and $I_2$ are calculated as the intersection points of a circle with the radius $FT$ and the commanded straight line. When the final distance as shown $I_2$-$C_2$ in Fig. 5 is shorter than $FT$, the next interpolation point from $I_2$ is generated at the interpolation point $I_3$ on the next tool path. In this case, the point $I_3$ is derived as the intersection between the circle with the radius $FT$ centered on the final interpolation point $I_2$ and the next tool path. Even in the case of the tool path by the circular interpolation command (G02/3), as the interpolation points are driven linearly, the same algorithm can be applied to the circular interpolation command (G02/3).

3.3 Calculation of estimated machining time

The machining time (moving time) $T_{pos}$ in the positioning command part (G00) is calculated using Eq. (1). The time $T_{pos}$ is derived as the times required for moving to the commanded points and confirming the positioning at the commanded points. The time required for the moving is obtained by dividing the total distance $L_i$ between the positioning commanded points by the maximum feed rate $F_{max}$ of the machine tool. In Eq. (1), $n$ is the number of the positioning command points in an NC program. The time required for the confirming the positioning is calculated by the in-position check time $T_{in}$ times $n$.

The machining time $T_{cut}$ in the cutting command part (G01/2/3) is calculated using Eq. (2). The interpolation points are predicted at each sampling time to control the position according to the above mentioned processes. In the Eqs. (2), $N_{g1}$, $N_{g2}$, and $N_{g3}$ are the total number of interpolation points of interpolation commands G01, G02, and G03, respectively.

$$T_{pos} = \sum_{i=1}^{n} \frac{L_i}{F_{max}} + T_{in} \times n$$  \hspace{1cm} (1)

$$T_{cut} = T \times (N_{g1} + N_{g2} + N_{g3})$$  \hspace{1cm} (2)
4. Estimation method of machining time using the high-accuracy profile machining function

4.1 High-accuracy profile machining function

In order to accurately estimate the machining time by the high-accuracy profile machining function, the detail algorithms and the control characteristics of the machine tool must be known. Since it is unusual to have such information, AI (artificial intelligence) technology has been applied. A neural network or deep learning can derive the target results by just knowing the relationship between input parameters and output parameters. The input parameters are set as the high-accuracy profile machining function parameters: shape correction utilization, process tolerance amount, program tolerance amount, a value obtained by dividing the cutting length by command speed, and the average command point distance. The output parameter is the machining time. Many network structures: NN, DNN, and deep learning, were confirmed from the viewpoint of the estimation accuracy of the machining time by trial and error. Then, the optimum structure of the network was determined.

An NC program including the many tool-path points to approximate profile shapes with short straight lines is often used to machine free-form surface such as dies/molds. The high-accuracy profile machining function is a control technique to realize machining with high speed and high accuracy. This function is performed the two sub-functions. The first is the shape correction sub-function which predicts the original shape in real time from the commanded points in an NC program according to the specified tolerance. The second is the shape adaptive control sub-function which generates the optimizing interpolation points for the tool paths determined by the shape correction sub-function. The high-accuracy profile machining function reconstructs the command tool paths in the NC machine tool controller to machine the shape in high accuracy and high speed. To employ the high-accuracy profile machining function, a user needs to set several parameters. Figure 6 shows the machining time when the same NC program is used with different parameters. The machining time significantly varies depending on the difference in the setting parameters, and the change is nonlinear for the parameters. For the interpolation control by the high-accuracy profile machining function, a DNN method was applied because the detail algorithm to determine the real tool paths by the function and acceleration/deceleration characteristics due to the control gains and the machine weight are not known. DNN is the useful tool to get the result by just using the relationship between input parameters and output result.

4.2 Deep Neural Network (DNN)

4.2.1 Configuration of DNN

The control algorithms for high-accuracy profile machining function are not open, and it is difficult to estimate the
machining time using the geometrical method. Hence, in this study, a machining time estimation method using the Deep Neural Network (DNN) which is one of Deep Learning based on the test data is proposed for the machining using the function. The hierarchical structure of the DNN designed in this study is shown in Fig. 7. It comprises input layer, hidden layers, and output layer. Each node in the layers is fully coupled between layers of the front and the rear. The input layer has the five input parameters for the nodes; Input 1 is shape correction utilization, Input 2 is machining tolerance amount, Input 3 is program tolerance amount, Input 4 is a value obtained by dividing the cutting length by the command speed, and Input 5 is the average command-point distance (the cutting length divided by the command point number). Inputs 1, 2, and 3 are parameters which influence the machining time among the setting parameters when using the high-accuracy profile machining function. Input 1: the shape correction utilization, means the correction degree for the original shape predicted from the command tool paths. Input 2: the machining tolerance amount, represents the allowable error during machining for the predicted original shape. Input 3: the program tolerance amount, is an approximation tolerance which is the setting parameter when creating the NC programs in the CAM system. Inputs 4 and 5 are the values calculated using the NC program. Input 4 represents the estimated machining time assuming that the effects of acceleration, deceleration, and the control parameters on the command cutting length are negligible. Input 5 means the complexity of the commanded tool paths. The output layer is the estimated machining time. To make the influence of each parameter equal when learning the data, these parameters are normalized; average value = 0 and standard deviation = 1. A hyperbolic tangent sigmoid transfer function was utilized as the activation function of each node. The back propagation is used as the learning method.

4.2.2 Learning data for DNN

To make the configured DNN, learning data is necessary. The learning data must be obtained under various conditions to improve the estimation accuracy of the DNN. Thus, the test experiments to obtain the learning data were conducted.
under the following procedure and conditions, and the machining time was measured. Figure 8 shows the target shapes with different curvatures prepared for the tests. The program tolerances 0.01 and 0.001 [mm] were set when the NC programs were generated. For the tests, 18 NC programs of a one-way scanning line of 5, 10, and 15 were generated. Table 1 lists the user setting parameters when using the high-accuracy profile machining function. The program tolerance set in using the function is the same as the tolerance set in generating the NC programs. A large amount of data is generated if the machining experiments are conducted for the combinations of all parameters; thus, we set them randomly, performed experiments with 130 combinations, and obtained the learning data.

**4.2.3 Optimization of configuration parameters**

The obtained learning data was applied to the DNN. The configuration parameters and the learning method significantly affect the output accuracy of the DNN. In this study, the grid-search algorithm was used to optimize the parameters: the number of hidden layers, number of nodes, and learning coefficients of the back propagation method. Table 2 lists each parameter to be evaluated. DNN Learning under all conditions shown in Table 2 was performed, and derived the correlation coefficient $R$ of the learning data and the output values. The parameters with the highest correlation coefficient $R$ are determined as the optimum configuration parameters of the DNN and the learning method.

Consequently, the number of hidden layers, number of nodes, and learning coefficient of back propagation method
were found to be 3, 4, and 0.1, respectively. To avoid excessive learning and obtain the appropriate number of learning iterations, the correlation coefficient $R$ was derived in learning iterations of 500, 1000, 4000, 7000, 10000, and 12000 under the determined parameters as shown in Fig. 9. When the learning coefficient is small, a considerable amount of time is required to learn because the correction amount to the weight calculated from the error is small. High learning coefficient makes the learning time short. However, if the learning iterations are increased considerably, the correlation coefficient $R$ becomes small because of excessive learning. According to the above results, the number of iterations of learning was determined to be 7000.

5. Verification experiment

A machining experiment was conducted to confirm the usefulness of the proposed machining-time estimation methods: the tool path prediction method and the DNN method. In the experiment to verify the tool path prediction method, the target shape is the shape B shown in Fig. 8 and the other conditions are given in Table 3. Figure 10 shows the actual machining time and the estimated times by the proposed method and the conventional method. In using the conventional CAM system, the estimation error rate was approximately 30%, whereas the estimation error rate using the proposed method improved to approximately 5%.

To confirm the viability of the proposed estimation method when using the high-accuracy profile machining function, the machining experiments and machining time estimation were performed for 20 patterns in which the parameters of the high-accuracy profile machining function were set randomly. The parameters are different from those of the learning data. Figure 11 shows the comparison between the actual and estimated machining times. Although the same NC program was used in a similar way for the different parameters of the high-accuracy profile machining function, the machining times are significantly different. However, the proposed method can accurately estimate the machining time. The average value of the error is approximately 3.4%.

Table 3  Experiment conditions

| Parameter          | Value       |
|--------------------|-------------|
| Tool radius        | 5 [mm]      |
| Command feed rate  | 4 [m/min]   |
| Tolerance          | 10 [$\mu$m] |
| Pick feed          | 1 [mm]      |
| Cutting amount     | 0.5 [mm]    |

Fig. 10  Result of machining time estimation
6. Conclusion

In this study, two methods to estimate machining time were proposed. One is the method based on predicting the actual tool paths of a smoothing function using the control characteristics of a machine tool. The other is the method using the DNN for using the high-accuracy profile machining function. The following conclusions were drawn from the machining experiments performed to confirm the usefulness of the proposed machining-time estimation methods.

1. The tool path was predicted using the linear and circular interpolation methods based on the smoothing function algorithms of a machine tool.
2. A machining-time was estimated according to the predicted tool paths of the linear and circular interpolations. The average value of the error was found to be approximately 5.0%.
3. By using the DNN, the machining time was accurately estimated for using the high-accuracy profile machining function.
4. The machining time estimation system was constructed by optimizing the DNN parameters.
5. The usefulness of the proposed machining-time estimation method using the DNN was confirmed through the machining experiments. The average value of the error was found to be approximately 3.4%.

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