Basic Study on Rapid Estimation of Machining Time Based on AI with Two-Dimensional Data (Trihedral Figures)

Hiroki Takizawa, Hideki Aoyama, and Song Cheol Won

Abstract—Machining time estimation is necessary for production scheduling, and it is important to answer the delivery date and price instantly when receiving an order from a customer. Currently, machining time is estimated by computer-aided manufacturing (CAM) system, but machining time estimation takes time for a numerical control (NC) program creation and machining simulation. Therefore, it is necessary to instantaneously estimate machining time. So, in this paper, we develop a system to estimate machining time instantaneously using artificial intelligence (AI), the input to the AI system was a trihedral figure of the shape to be removed, and the output was machining time (in intervals of 15 minutes). In this paper, we used convolutional neural network (CNN) which is a kind of AI and effective for image recognition, and estimated the machining time. Then, we created the shape to be removed by creating the required shape (machine parts) and the material shape (rectangular prisms) arbitrarily as the machining data, and estimated the machining time from the removal volume, and constructed the data set. An evaluation experiment was performed to allow AI to train 1082 images of the trihedral figure of the shape to be removed and confirm the estimation accuracy of the machining time. As a result of conducting evaluation experiments, it was possible to obtain a machining time estimation result within 15 minutes of prediction error in all 70 evaluation data. In this paper, the outline of the proposed method, the method of creating the machining data of self-made, and the method of constructing the optimal CNN are described in order, and finally, the results of the evaluation experiment are summarized.

Index Terms—Artificial intelligence, image processing, machining time estimation, trihedral figure.

I. INTRODUCTION

It is necessary to make scheduling in order to realize efficient production [1]. Machining time estimation is essential for scheduling because it provides manufacturing engineers with information to accurately predict the productivity of a machine tool and to make optimum scheduling [2]. When the production schedule changes, it is necessary to reschedule production flexibly and quickly. Also, when receiving a part machining order from a customer, it is necessary to reschedule based on a machining time

estimation and to give a delivery date and price instantly.

However, due to the complexity of NC machining processes, combination of multiple factors, as well as the dynamics of manufacturing environments, it is difficult to achieve an accurate machining time estimation of complex parts. NC machining time of a part mainly depends on its geometry information, process plan, NC program, and machine characteristics. Existing commercial software tools and research prototype systems do not fully consider these factors [3]. At present, machining time is generally estimated by a computer-aided manufacturing (CAM) system. In this case, machining time is simply calculated by creating a numerical control (NC) program for machining and then dividing the total command distance by the command speed value on the NC program and multiply by the coefficient [4]. Therefore, they cannot provide accurate estimation. As a result, there is a problem in that a large estimation error occurs due to control characteristics of the machine tool, and the NC program generation and machining simulation are very time consuming.

In fact, it is demanded for salesmen belonging to production companies to instantaneously answer the delivery date to customer's requests. Assuming that an accurate estimate is made using a CAM system, a rapid estimation of the machining time is required in order to answer a rough delivery date at the sales spot. Therefore, there is a need for a method for estimating machining time without generating NC programs.

In this research, we proposed a rapid machining time estimation method using artificial intelligence (AI) without generating NC programs.

Machining time depends on parameter such as command speed and tool diameter, but in this research, it is assumed that these parameters depend on the shape of the workpiece before and after machining. Therefore, without creating an NC program, machining time is estimated based on a two-dimensional drawing (trihedral figure) of the shape to be removed.

In this research, machining time is estimated based on the past machining data at the manufacturing factory. With the conventional method, the control characteristics of the machine tool cannot be taken into account, resulting in a large estimation error. However, with the proposed method, machining time is estimated based on the past machining time at each manufacturing factory including the control characteristics of the machine tool, so the proposed method is expected to improve machining time estimation accuracy. Finally, we confirm the accuracy of the proposed method through experimental evaluation.

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II. MACHINING TIME ESTIMATION USING AI

A. Summary of the Proposed Machining Time Estimation Method

We developed an AI system to rapidly estimate machining time. The input data to the AI system is a trihedral figure image of the shape to be removed generated by subtracting the required shape from the material shape, and the output data is the estimated machining time with intervals of 15 minutes. Fig. 1 shows the process flow of the proposed method.
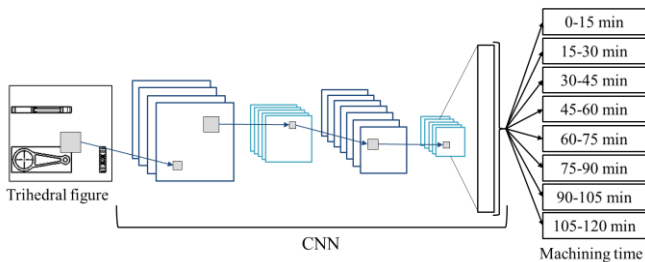

Fig 1. Process flow of the proposed method.

The reason for selecting a trihedral figure image of the shape to be removed as the input data is that there is a certain correlation between the shape to be removed and machining time [5].

An AI system trains a large set of trihedral figure images of shapes to be removed and machining times to construct the trained AI system. The estimated machining time is output by inputting a trihedral figure image to the trained AI system.

In this research, we use a convolutional neural network (CNN), which is a kind of deep learning, to estimate machining time. Deep learning is defined as machine learning using multi-layered neural networks and has attracted attention in recent years. In image recognition, because deep learning defines features automatically and has calculations in each layer, it is not necessary for image features to be predetermined. A CNN is a type of deep neural network whose structure consists of alternately stacked convolution and pooling layers [6], [7]. This structure models the receptive field in the human visual cortex and is known to achieve high performance in the field of image recognition [8]. So, a CNN is used to estimate machining time.

B. Preparation of Training Data

The training data is a data set of trihedral figure images and machining times. In order to build a CNN, it is necessary to prepare training data. When implementing a CNN, it is assumed that an actual data set is used and held on a manufacturing factory. The actual data set contains a combination of shapes to be removed and machining time required for actual machining, and the shapes to be removed are stored as trihedral figures.

In this research, it was difficult to collect an actual data set, so required shapes (machined shapes) and material shapes were arbitrarily created to generate the shape to be removed, and the machining times were estimated from the removed volumes. In order to generate the data set, 546 required shapes were constructed by defining seven types of shapes, as shown in Fig. 2, and changing the shape parameters (inner diameter, outer diameter height, width, etc.). The 546 required shapes are shapes with a slight change from each basic model.

In addition, material shapes (rectangular prisms) were defined in consideration of the required shapes. The material shape is the shape of the work material before machining. In this research, all material shapes are defined as rectangular prisms. As with the required shape, a total of 21 material shapes were prepared by setting shape parameters. As shown in Fig. 3, the trihedral figures of the shapes to be removed are generated by subtracting the required shape (Fig.3 (b)) from the material shape (Fig. 3 (a)) using 3D computer-aided design (CAD) and deriving the shape to be removed (Fig. 3 (c)). As a result, 1082 data sets of trihedral figures and their machining times were constructed by combining the required shapes and material shapes. Table I shows the number of the shape to be removed corresponding to each basic model of required shapes. A total of 1082 shape data shown in Table I were trained by AI.

TABLE I: THE NUMBER OF TRAINING DATA

Basic model of required shapes	(a)	(b)	(c)	(d)	(e)	(f)	(g)	Total
The number of training data	185	160	200	137	105	135	160	1082

The trihedral views of each shape to be removed were made by the following procedure:
(1) Create a constant-scale trihedral figure of the shape to be removed using 3D CAD. In this research, the scale was 2:1.
(2) Save the trihedral figure obtained in (1) as a JPEG image.
(3) Crop the image obtained in (2) to the specified size (150 × 190 pixels).
(4) Binarize the image obtained in (3) for the purpose of the clarification of the trihedral figure of shape to be removed features.

In order to shorten the calculation time, the RGB values of the trihedral figures were discarded and converted to grayscale images. The trihedral figure is input as image data to AI (Deep Learning). Fig. 4 shows the trihedral figures actually used for training. The generated 1082 shapes to be removed were all converted to a trihedral figure by the above procedures, and input images were prepared.

The machining time was determined by dividing the removed volume by a constant cutting rate (cutting volume per unit time); in this research, we refer to this value as the virtual machining time. Based on the calculated virtual machining times, by giving suitable machining time in intervals of 15 minutes to each trihedral figure, training data are created.

Through the above procedures, 1082 trihedral figures of shape to be removed and corresponding machining time were obtained respectively, and a data set used for AI training was created.

C. Construction of the CNN System

The prediction accuracy of an AI system largely depends on the structure of a CNN. Therefore, it is necessary to determine the optimal structure of a CNN. The created 1082 trihedral figure images are randomly divided into 1061

training data and 21 verification data. The many structures of the CNN were tried, and the optimal structure of the CNN was determined based on the correct answer rate of the verification data obtained from each structure.
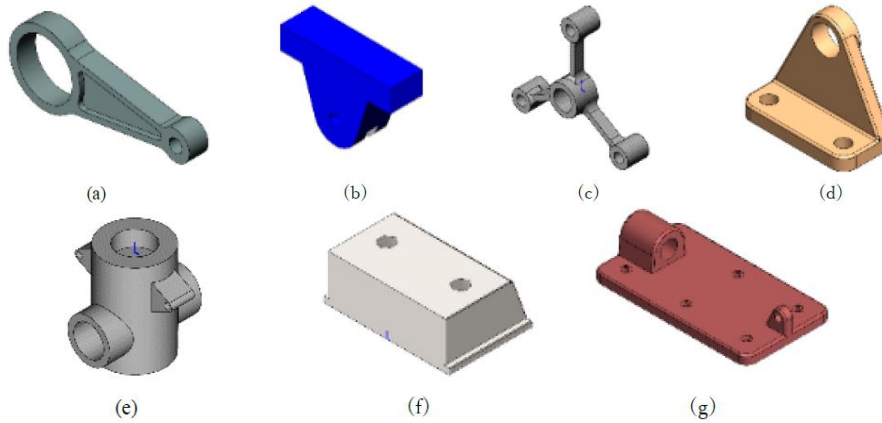

Fig. 2. Basic model of required shapes.

TABLE II: STRUCTURE OF CNN

No.	Layer	Filter size	Stride	Size
1	Input layer	-	-	(150,190,1)
2	Convolutional layer 1	(2,2)	(1,1)	(149,189,10)
3	ReLU layer 1	-	-	-
4	Convolutional layer 2	(2,2)	(1,1)	(148,188,10)
5	ReLU layer 2	-	-	-
6	Convolutional layer 3	(2,2)	(1,1)	(147,187,10)
7	ReLU layer 3	-	-	-
8	Max pooling layer	(2,2)	(2,2)	(74,94,10)
9	Fully connected layer	-	-	(128)
10	Output layer	-	-	(14)

In determining the structure of the CNN, the number of layers, the combination of layers, the filter size and the number of filters of the convolutional layer, the filter size of the pooling layer, and the number of nodes in the fully connected layer were optimized as parameters. In addition, the optimal values of the initial training rate, the epoch, and the mini-batch size were determined as hyperparameters (parameters related to training).

Fig. 3. Creating a shape to be removed.

Fig. 4. Trihedral figure.

Table II describes the structure of the CNN constructed in this research. It consists of seven layers: an input layer, convolutional layers, a maximum pooling layer, a fully connected layer, and an output layer. The input layer is a 150 × 190 pixels trihedral figure, and the size of the output layer is 14 (machining time in intervals of 15 minutes). The convolutional layer and the max pooling layer are characteristic layers in the CNN, and their number and combination have a great influence on the prediction accuracy. In addition, a ReLU layer is used as the activation function to determine the output value of the convolutional layer in order to speed up the learning and calculation speeds. The initial learning rate was set to 0.0125, and it was multiplied by 0.5 every 10 learning sessions. The epoch was set as 30 times, and the stochastic gradient descent method was used as the learning algorithm. The mini-batch size, which is the number of data used to update the weight at one time, was set to 30.
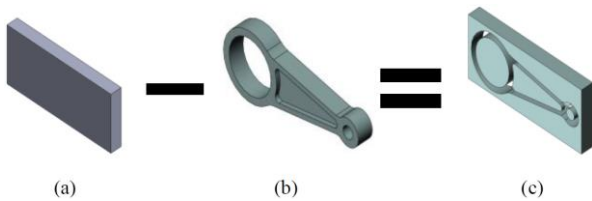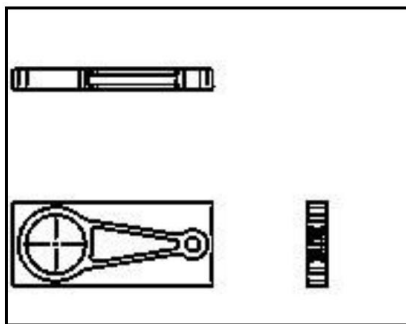
III. EVALUATION OF CONSTRUCTED CNN

In order to confirm the usefulness of the proposed method, machining time estimation evaluation experiments were conducted using the constructed CNN.

70 required shapes similar to those used as training data were prepared as evaluation shapes to evaluate the proposed CNN. Then, the material shapes were set for each required shape. Of the 70 evaluation shapes, the virtual machining time of 35 of them (test group A) was approximately the median of the machining time divided by 15 minutes. For the

other 35 (test group B), the virtual machining time was approximately the boundary value of machining time divided by 15 minutes.

Trihedral figures of the shapes to be removed from test groups A and B were input to the constructed CNN, and the machining time was estimated. Then, the estimated machining time and virtual machining time were compared, and the estimation accuracy of the constructed CNN was evaluated.

The estimated accuracy of each test group is shown in Table III. The estimation accuracy for the required shapes in test group A was 100%, and that for the required shapes in test group B was 89%. Fig. 5 and Fig. 6 show the transition of epochs and the correct answer rate for each test group. From these figures, it can be seen that as the number of epochs increases, both the correct answer rate of the training data and the test data increase, and it is possible to estimate the machining time from the trihedral figure of the shape to be removed using CNN.

For test group A, both training data and test data have been trained with a correct answer rate of 95% or more. On the other hand, test group B has finished training with a correct answer rate of about 100%, while test data has finished training with a correct answer rate of about 90%. This is considered to be because the test group B was difficult to classify since the virtual machining time of test group B was set to the boundary value of machining time in intervals of 15 minutes.

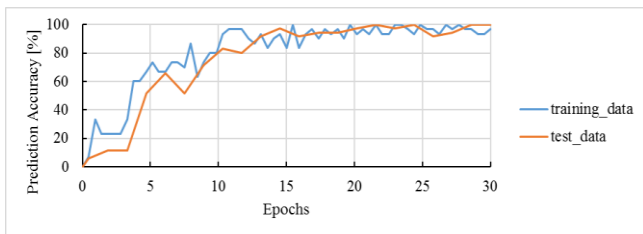TABLE III: ESTIMATION ACCURACY

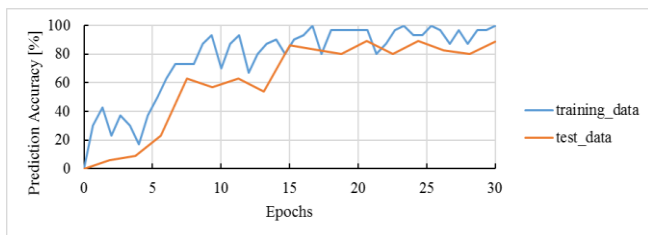| Test group A	Test group B
100 %	89 %

Fig. 5. Prediction result on test group A.

Fig. 6. Prediction result on test group B.

TABLE IV: INCORRECT ANSWER DATA

Test data No.	1	2	3	4
Machining time [min]	29.5	122.6	119.7	59.995
Machining time (in intervals of 15 minutes) [min]	15-30	120-135	105-120	45-60
Estimated machining time [min]	30-45	105-120	120-135	60-75

In fact, 4 of the 35test data resulted in incorrect answers. Table IV shows the incorrect answer data. As you can see

from this table, all incorrect answer data were estimated within 15 minutes of the correct answer. Therefore, even if we make a production scheduling based on this estimation result, it is considered that there are few problems in production scheduling. Also, it is considered that estimation accuracy can be improved by setting the increment of the output machining time to be small (for example, five minutes). In addition, AI takes time to train, but once training is completed, the output value (machining time in intervals of 15 minutes) can be calculated instantaneously by inputting a trihedral figure of the shape to be removed. Even when using a CAM system, an estimation error of nearly 50% may occur, and a certain result was obtained in the estimation accuracy, and we can confirm the usefulness of this system.

In addition, when introducing this system in the manufacturing factory, it is assumed that the actual data of the manufacturing factory is trained, so further improvement in estimation accuracy can be expected.

IV. CONCLUSION

In this paper, we proposed a rapid estimation method for machining time. We built a CNN whose input is a trihedral figure of shape to be removed, and output is machining time (in intervals of 15 minutes) based on the virtual machining data as a basic step. Then, the optimal structure of the CNN was constructed by determining the optimum value of each parameter that affect the estimation accuracy of the machining using the prepared 1082 trihedral figures. After that, the prepared 1082 trihedral figures were trained by CNN, and 70 evaluation shapes were input to the constructed CNN. As a result, it was possible to output the estimation result within 15 minutes. Moreover, since the machining time could be estimated instantaneously by using a CNN, the usefulness of the proposed method could be confirmed.

There are two types of machining processes: roughing and finishing. Therefore, in the future, considering the characteristics of the machining time of these two types of machining processes, it is necessary to consider the input data related to the machining time.

In addition, since machining conditions such as feed rate and tolerances have a large effect on machining time, we plan to construct a neural network that inputs these parameters in addition to images. We want to estimate the machining time in consideration of the machining process and machining conditions, and improve the estimation accuracy for more complex required shapes.

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