# Development of Learning System with Process Model Selection for Control of Ball-End Milling

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The situation of ball-end milling varies during the process with the change of cutting conditions. These variation should be considered in order to control the ball-end milling. Cutting simulation is one of effective method to understand the variation during the process. It is, however, difficult to determine the process model for simulation a priori. Thus, it is desired to construct the process model by learning from actual milling process. This paper presents a learning system with process model selection. The system controls ball-end milling process by using simulation result, and also acquires process model from actual milling data. Developed milling simulator provides the function of geometrical and physical simulation. Process models are acquired by learning using a mathematical programming method. The results of experiments by a prototype system show that cutting forces can be predicted for various cutting conditions.

## 1. INTRODUCTION

The sophisticated control methodologies have been developed and been applied to machine tools to produce the various types of machined products, so far. Simulation based control method is understood as one of useful method [1]-[6].

In spite of lots of works, there are two unsolved basic problems. First problem is that most of all simulation based control researches can be applied to square-end milling only, and few researches deal with ball-end milling[3][4]. Second problem is the lack of systematic approaches to construct process model. Systematic approaches have been studied in turning only without any geometrical model[5][6].

More sophisticated control methodologies are required to realize more flexible and high efficient machining. These methodologies should have a capability of dealing with ball-end milling in conventional manner.

This paper shows the development of learning system with process model selection in order to overcome the above problems. The system has functions of simulation based control for ball-end milling, and also has the functions to acquire the process model from actual milling data.

In Section 2, framework of developed learning system is described. In Section 3, ball-end milling process is modeled with respect to the geometrical shape of workpieces and cutting force. Furthermore, a method to modify NC data based on a simulation result is described. Process model acquisition using a mathematical programming method is discussed in Section 4. In Section 5, configuration of experimental system is explained and the result of experiments which show cutting force can be predicted for various conditions are presented.

## 2. FRAMEWORK OF LEARNING SYSTEM WITH PROCESS MODEL SELECTION

Figure 1 illustrates a framework of learning system with process model selection. As shown in Fig. 1, developed system has two phases : cutting phase and learning phase.

Cutting phase consist of process planning, cutting simulation, NC data generation, and machining. Especially, cutting simulation is fundamental function in the cutting phase. In this research, the process is assumed to be described as a collection of process model which can be used in a certain situation. The collection of process model is stored in the model base. At first, default process model is used for the simulation.

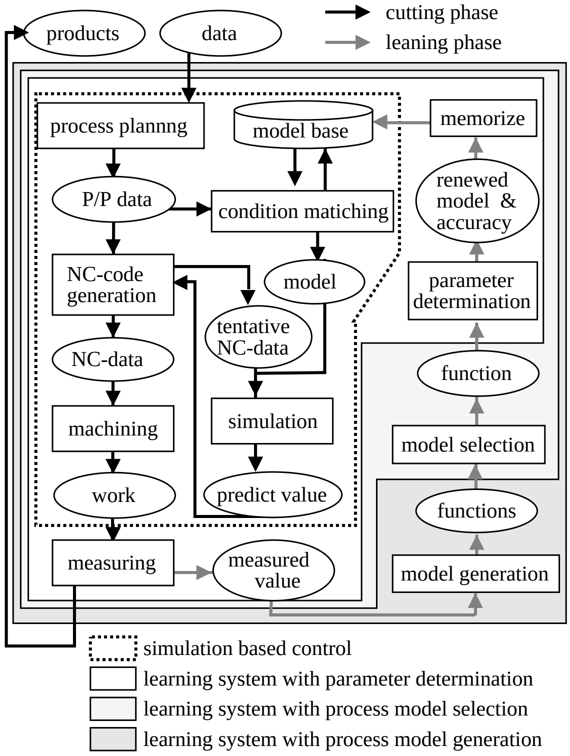


Figure 1. Framework for learning system with process model selection

After machining in various cutting conditions, most desirable process model is selected from the model base and the selected one is used for the simulation. Scheme of cutting phase is called simulation based control method.

In learning phase, a process model is acquired from measured sensory data for each cutting condition. These acquired models are stored in the model base and will be used in a future simulation. There are three levels in learning system : learning system(LS) with process model generation, LS with process model selection, and LS with parameter determination. They have the different levels of automation. First system has the abilities to extract the influence factors from the measured data and discover the mathematical functions. Second one has ability to select a suitable function among acquired multiple process models. Third one has ability to determine the process model parameters from measured data.

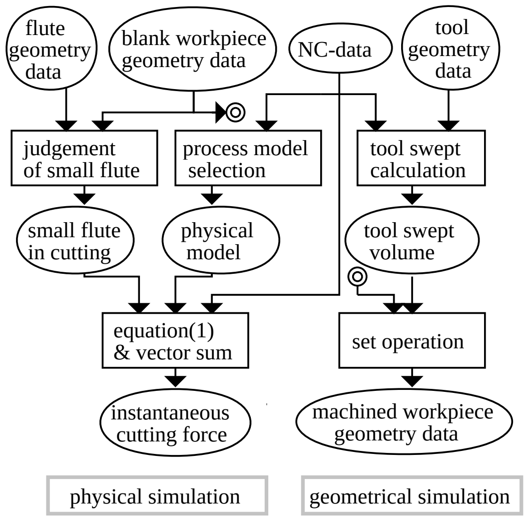


Figure 2. Processing flow of cutting simulation

In general, model generation is difficult problem for computers. Thus in this paper, it is assumed that various models are generated by empirical knowledges and know-hows a prior. Then, model selection and parameter determination are considered as the problem of learning system with process model selection.

## 3. SIMULATION BASED CONTROL

### 3.1. Modeling of ball-end milling process

Simulation based control uses the predicted values of cutting force, machining error, tool life and so on. In this paper, ball-end milling process is modeled with respect to the geometrical shape of workpieces and the cutting force. Geometrical shape is indispensable information, since it is generally difficult to control ball-end milling process in an empirical method due to the complex shapes of workpieces. Furthermore, cutting force is one of the most important physical information because it has essentially related to tool deflection, chattering, tool wear, and so on.

Developed simulation flow is shown in Fig. 2. Process simulation consists of geometrical simulation and physical simulation. The shape of a machined workpiece is evaluated in the geometric simulation and cutting force is computed in the physical simulation.

#### 3.1.1. Geometrical simulation

Machined workpiece geometry can be expressed as a Boolean subtraction of the tool swept volume geometry from blank workpiece geometry. Furthermore, the cutting part of flute is approximately detected by judgement whether small flute is inside of workpiece or outside. The choice of geometrical expression is important since the process simulation requires a lot of geometrical computations. Many geometrical models have been proposed, so far. The following features are important to calculate the geometrical shape in ball-end milling process.

- There is a unique tool swept volume correspond to every surface point.
- Every tool swept volume is expressed as the set of simple mathematical function.
- Expression of tool swept volume can be known a prior.
- Boolean subtractions and judgement of flute must be calculated fast.
- High geometrical accuracy is required.

Considering the above features, geometrical shape is expressed by 2-dimensional array which contains geometric properties for all pixels. This method is called G-buffer[7] or P-map[8]. In this case, geometric property is given by the mathematical expression of tool swept volume. This method can be applied to other tools easily.

Figure 3 shows the comparison between Z-map expression and used expression. Cutting processes are expressed by renewaling the memory of the recent number of tool swept volume for each machined pixel. Pixel size must be determined small enough to express required accuracy. At least, cusp height must be expressed so that the accuracy can be evaluated in the simulation.

#### 3.1.2. Physical simulation

Before physical simulation, a desirable process model is selected. Then, physical simulator use the process model and predict instantaneous cutting force for each rotational angle.

In physical simulation, cutting force is computed as the vector sum of all small forces loaded on individual divided small flutes. Geometric model described in the previous section is used in order to examine whether each flute interferences the workpiece or not. Small forces corresponding to each flute are computed using the physical model. Let us use a simple two-dimensional cutting model in a plane perpendicular to flute.

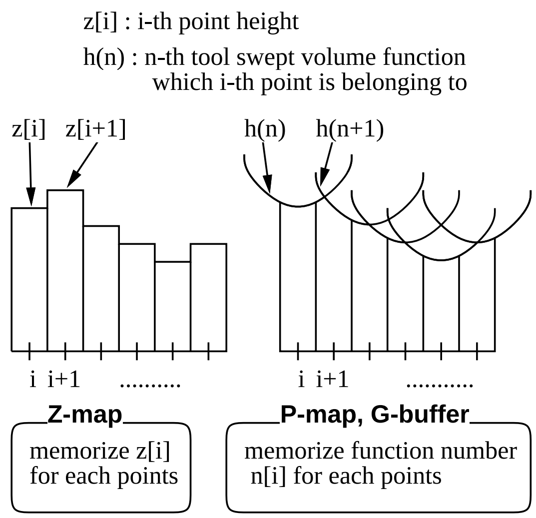


Figure 3. Comparison of geometrical expression

Small force $f_v$ parallel to movement of each cutting flute and $f_f$ perpendicular to movement are expressed as follows:

$$\begin{Bmatrix} f_v \\ f_f \end{Bmatrix} = \begin{Bmatrix} (c_1 + \frac{c_2}{h}) \cdot (1 - c_3 \cdot V) \\ (c_4 + \frac{c_5}{h}) \cdot (1 - c_6 \cdot V) \end{Bmatrix} \cdot \Delta A \quad (1)$$

where $\Delta A$ is a cutting area, $h$ is equivalent cutting depth, $V$ is cutting velocity, and $c_1$ through $c_6$ are parameters. Parameters $c_1$ through $c_6$ are determined by cutting conditions and selected based on situation similarity. In this research, similarity is defined as Euclid norm of the cutting conditions and the tool movement direction.

Calculated small forces by equation (1) are evaluated with reference to the absolute coordinate system. These small values are summed up to derive cutting force. In this paper, two-dimensional cutting model is used. More precise models such as oblique cutting model are also applicable in the physical simulation.

An example of graphic output during the simulation is shown in Figure 4.

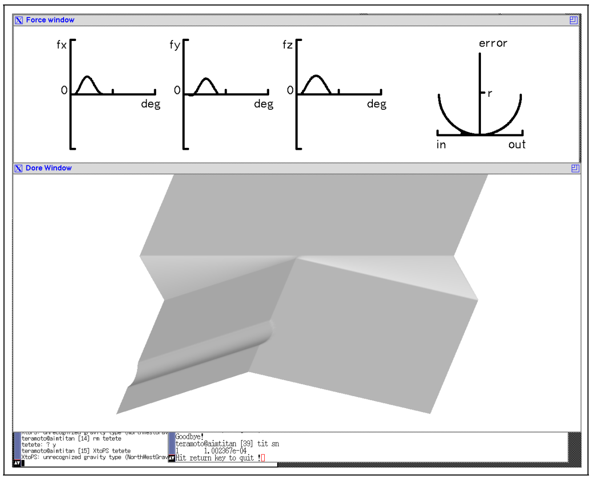

Figure 4. Example of CRT display

### 3.2. NC data modification based on simulation result

NC data is modified a priori in order to improve control robustness[1][2]. For a new situation, one process model must be chosen in simulation. In this approach, a process model corresponding to a new situation is assumed to be the process model which is acquired in most similar situation. Then, the accuracy of the simulated results limited. Usually, simulation base control method trusts the predict values perfectly. In this case, however, the model accuracy must be taken into consideration when the simulation results are used. Accuracy is defined as the function of situation similarity and regularized residual computed in the learning process. Figure 5 illustrates the procedure of NC data modification.

## 4. LEARNING SYSTEM WITH PROCESS MODEL SELECTION

It has been recognized that the feedback of actual process information into simulation is effective in order to improve the simulation accuracy[1]. Recently, Matsumura et al proposed the concept of "adaptive prediction" and constructed a prototype system for turning process[6].

Figure 6 shows the processing flow of the learning system. Physical model is acquired from measured data. In this study, a mathematical programming method is adopted to calculate the

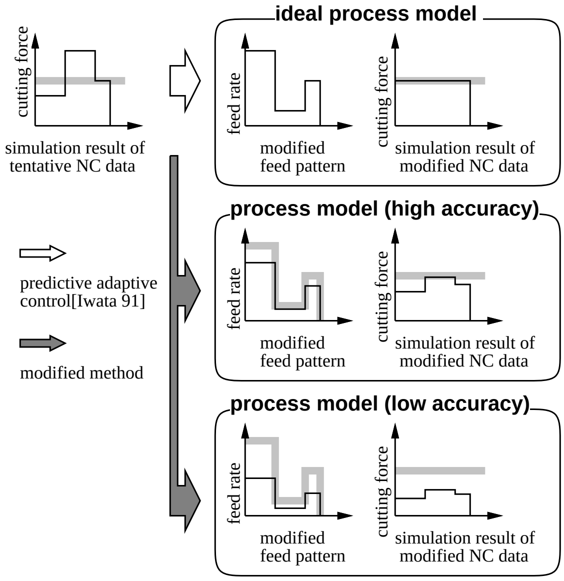


Figure 5. Pre-process NC data modification

model parameters. Quasi-Newton method is used to minimize the residual. The residual $R$ is given as follows:

$$R = min(R_1, \ldots, R_M)$$

$$R_j = \sum_{i=1}^{N} \|\hat{F}_i - f_j(X, C)\|$$

where $\hat{F}_i$ $(i \in [1, N])$ are measured data, $f_j$ $(j \in [1, M])$ are mathematical functions of physical model, $X$ is the machining condition set, and $C$ is the model parameter set. A physical model function that minimizes the residual is selected as suitable function among the known functions.

The process model corresponding to the current condition is stored in model base by memorizing a set of the new process model, model parameters, and cutting conditions.

Memory-based learning method is applied in order to store the acquired model and parameters. The method is fast and never overlearn. Furthermore, it is easy to evaluate the learned result since process models are memorized in explicit forms.

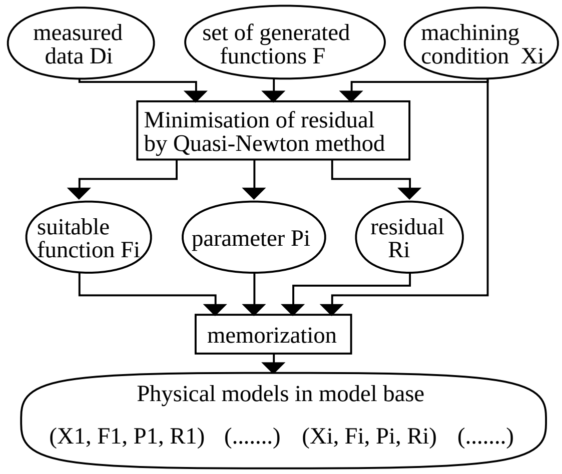


Figure 6. Processing flow of learning

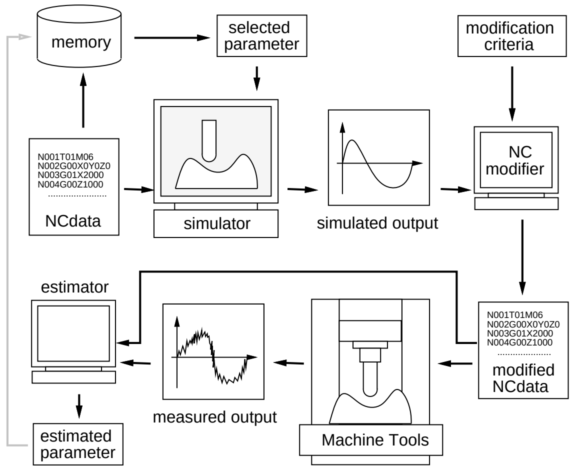


Figure 7. Configuration of prototype system

## 5. EXPERIMENTAL RESULTS AND DISCUSSION

### 5.1. Experimental system

Figure 7 illustrates the configuration of prototype system developed in this study. The system can be divided into four major modules: machining simulator, NC data modifier, machining center with a CNC controller, and model maintenance module.

Procedure of learning system is as follows:

1. Process model and parameters are selected from model base constructed in memory, considering the model accuracy and condition similarity.
2. Cutting force is predicted using machining simulation.
3. NC data is modified to maximize the feed rate within the criteria of cutting force.
4. Cutting force is measured in machining and compared with predicted force.
5. New process model parameters are calculated form measured data using a mathematical programming method.
6. Calculated parameters and residual are memorized with cutting conditions as the index of memory.

### 5.2. Experimental results

To evaluate the ability of prediction, cutting force is measured and is compared with simulation result. Experimental conditions are listed in Figure 8. For the measurement of instantaneous cutting force, 3-dimensional dynamometer is mounted on the machining center. Comparison between measured data and simulation result is shown in Figures 9 and 10.

Two types of simulation are performed. One simulation uses the process model acquired from preparatory experiments(model-1). Another simulation uses the process model acquired from one actual machining data measured at a different feed rate(0.1mm/rev)(model-2).

From the experiment results, both of simulation results are within 25% in accuracy. Adaptation of more precise model is future works.

## 6. CONCLUSIONS

Learning system is studied in order to adapt simulation based control method into actual ball-end milling process. Algorithm of learning system with process model selection is proposed.

A prototype system is developed. The experiment results show, 1) cutting force is predicted within 25% in accuracy, 2) learning system is effective because there is no need to make the preparatory experiment for the model building.

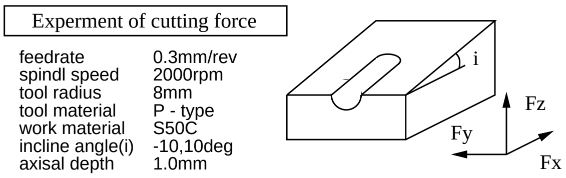


Figure 8. Cutting conditions in experiment

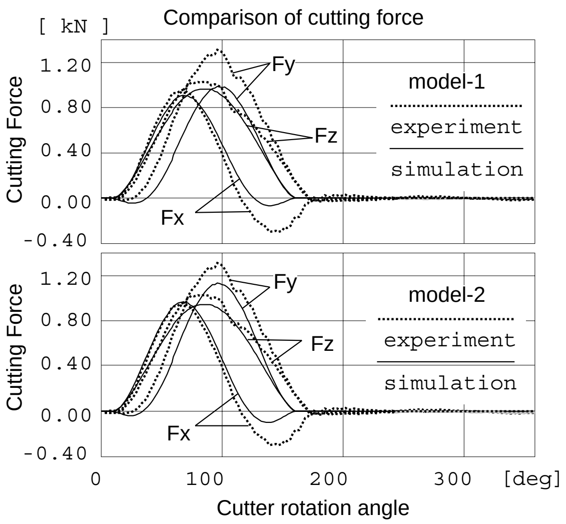


Figure 9. Comparison of cutting force (+10[deg])

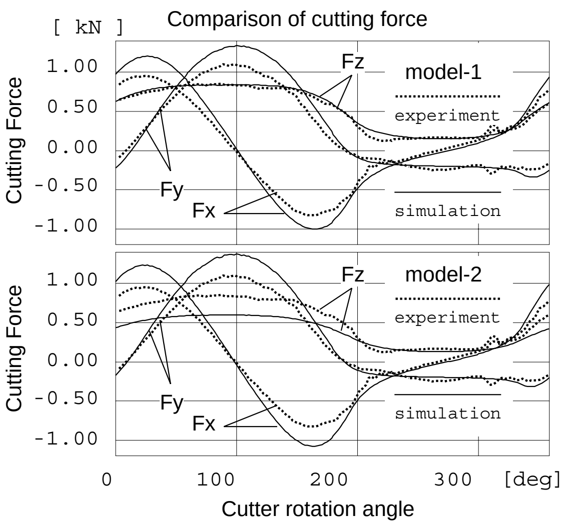


Figure 10. Comparison of cutting force (–10[deg])

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