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MODEL-BASED LEARNING CONTROL OF CUTTING FORCES IN END MILLING PROCESSES

Soichi Ibaraki, Takashi Ogawa, Atsushi Matsubara, Yoshiaki Kakino
Department of Precision Engineering, Kyoto University
Yoshida-honmachi Sakyo-ku Kyoto, Japan 606-8501
Email: ibaraki@prec.kyoto-u.ac.jp

ABSTRACT

In order to fully utilize the potential of high-speed machining centers for high productive machining, the optimal process design is a critical issue. In particular, this paper considers the feedrate optimization in end milling processes based on the cutting force control. Compared to feedback control approaches that are often found in the literature, a model-based feedforward control approach is simpler, but has an inherent advantage especially when the process is subject to quick change. This paper proposes an iterative model updating method, which allows the model-based feedforward approach to have the adaptability to unmodelled processes to some extent. Starting from the initial model, which is provided from the database, the process model is updated at each machining cycle, and consequently, the control law is improved in an iterative learning manner. Taking a pocket machining as an example, the proposed scheme is implemented within the following three canned milling cycles: 1) corner rounding, 2) internal cylindrical machining by spiral cycles, and 3) slot milling by trochoid cycles. The practical applicability and effectiveness of the proposed approach are verified in experimentation.

Key Words: Cutting force control, milling processes, model-based feedforward control, iterative learning, canned cycles.

1 Introduction

Recent technological development has commercialized high-speed machining centers of the feedrate up to 60 m/min, the acceleration rate up to 1 G, and the spindle speed up to 20,000 rpm. In today's manufacturing industry, however, such high-speed, high-acceleration machining centers are not widely accepted except for some specialized uses, such as the manufacturing of a cylinder head of automobiles [1]. In order to optimize the productivity while meeting the requirement for machining accuracies, the optimal process planning is a critical issue. In today's industry, the process planning relies to a high extent on expert machine operators' experience and knowledge. Due to the lack of their experiences on high-speed machining, the process planning to fully utilize the potential of high-speed machining centers is quite difficult even for expert operators.

There have been efforts to develop a database of optimal machining parameters. However, it is practically impossible to develop a database that covers any possible machining processes. Particularly in parts manufacturing, the number of possible combination of tool and workpiece material is generally too many to cover, and new tools and workpiece materials are being actively introduced into today's market. Furthermore, the characteristics of workpiece material could vary in every lot, and the progress of tool wear or the difference in each machine setup also affect the machining dynamics.

Adaptive control approaches in machining processes have been studied since the 70's as an alternative strategy to optimize machining conditions without having a large database. Our research group has developed an intelligent adaptive control system for drilling and tapping processes [2; 3]. It was successfully implemented in commercial machining centers. The importance of process control in end milling processes has been also widely recognized. Although it is generally a more challenging issue than in drilling or tapping cases, a considerable number of research efforts have been dedicated to the cutting force control in end milling processes. Most approaches found in the literature are adaptive feedback control schemes [4; 5; 6; 7].

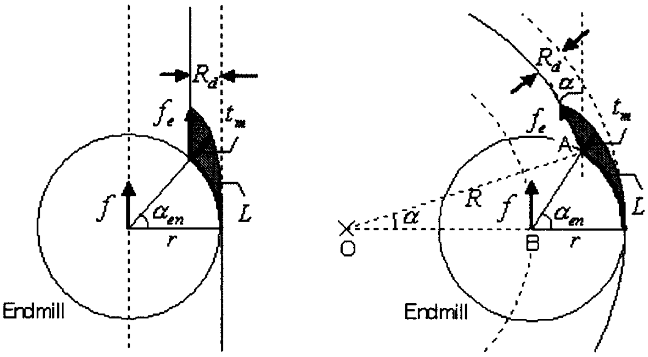
An inherent problem of any feedback control approaches is its control delay. If the sensor delay, the calculation delay, and the actuation delay are negligibly small compared to the change rate of machining dynamics, then an adaptive control scheme would be an effective tool to handle critical problems such as tool breakage, tool wear, and low productivity due to too conservative cutting conditions. However, due to technical and cost constraints, it is impossible to completely eliminate the control delay. As a result, in practical applications, there are cases where any feedback control schemes cannot achieve satisfactory control performance, especially when the process is subject to quick change. For example, in our experiences, typical feedback control schemes cannot meet performance requirement at a sharp corner (see Section 3.3), or on a curve where the cutting force changes continuously and quickly (see Section 3.4).

This paper presents a feedforward control scheme based on the model-based prediction of cutting forces. If the exact process model is known, one can optimize the feedrate *in advance* such that the cutting force is regulated at the desired level. Despite of its simplicity, it has a strong advantage to address the above problem. That is, by using a priori knowledge on the tool path, the process change can be predicted before it is actually observed. Unlike feedback control approaches, the time delay in the control system is a less critical issue, because it can be easily compensated.

The performance of such a model-based feedforward-type control approach completely depends on the accuracy of the prediction model. In the literature, a considerable number of cutting mechanism models have been proposed over the past several decades (e.g. [8; 9]). Most of the proposed models are complex, and include too many parameters to be identified. They are often used for analysis or simulation purposes, but not for the control purpose. In this paper, we employ a simplified model proposed by Kakino et al. [10; 11]. Although the simplified model does not offer much insight into physical cutting mechanism, its validity to predict cutting forces was verified by extensive experiments in [10; 11]. A feedrate profile at the first cycle is optimized based on the initial model, which is provided from the database. As machining cycles are iterated, the prediction model is updated at each cycle, and consequently, the control performance is improved in an iterative learning manner. The proposed learning scheme allows the model-based feedforward control approach to have the adaptability to unmodelled processes to some extent, which is an inherent advantage of feedback control approaches.

The objective of our project is to implement the proposed control scheme within canned milling cycles. At this stage, such implementation is more practical than to implement a process control system that works under arbitrary NC programs. We mainly consider a rough cutting or intermediate cutting processes in parts manufacturing.

The remainder of this paper is organized as follows. The next section first reviews the prediction model of cutting forces in end milling processes, and then presents the proposed model-based learning control scheme. Section 3 presents three case studies of the proposed method implemented in canned milling cycles. Section 4 gives the conclusion of this paper.



(a) On a straight path (b) On a circular path

Figure 1. Schematics of end milling process

2 Model-based Learning Control of Cutting Forces in End Milling Processes

2.1 Process Model and Feedrate Optimization

Figure 1(a) and (b) depict schematics of end milling processes on a straight path and a circular path, respectively. In the figures, t_m and L respectively denote the maximum undeformed chip thickness and the arc length of cutting engagement. Kakino et al. [10; 11] proposed a simple "response surface" model [12] to predict the cutting force by using these two variables:

$$\hat{F} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_{11} X_1^2 + \beta_{22} X_2^2 + \beta_{12} X_1 X_2 \tag{1}$$

where X_1 and X_2 respectively represent the variables, t_m and L, normalized by given central values. When six coefficients $(\beta_0, \beta_1, \beta_2, \beta_{11}, \beta_{22}, \beta_{12})$ in Eq. (1) are properly identified, its validity to predict the cutting force (either the tangential force, F_t, the normal force, F_n, or the combined force, $F_c = \sqrt{F_t^2 + F_n^2}$) has been verified by extensive experimentation in [10; 11]. In [10; 11], the coefficients are identified by conducting a set of machining tests. A simple straight path is repeatedly machined with different combination of the radial depth of cut and the feedrate, i.e. different combination of t_m and L. The coefficients are identified based on the steady-state cutting force measured in each test.

From the geometry shown in Figure 1, the following equations can be derived:

$$\begin{aligned} L &= r\alpha_{en} \\ t_m &= f_e \sin(\alpha_{en} - \alpha) \\ (R - R_d)^2 &= (R - r)^2 + r^2 + 2(R - r) r \cos(\alpha_{en}) \\ \sin(\alpha) &= \frac{r \sin(\alpha_{en})}{R - R_d} \end{aligned} \tag{2}$$

$$f_e = f\frac{R-R_d}{R-r}$$

where f_z: the feed per tooth at the tool center (mm/tooth), f_e: the feed per tooth at the engagement point (mm/tooth), α_{en}: the engagement angle (rad), α: the angle between the directions of f_z and f_e (rad), R: the arc radius (mm), R_d: the radial depth of cut (mm), and r: the tool radius (mm) (see Figure 1).

Suppose that R, R_d and r are given along the tool path. When the desired cutting force level, F_{target} (N), and the model (1) are given, the optimal feedrate, f^* (mm/min), to regulate the cutting force at $\hat{F} = F_{target}$ can be uniquely determined by using the equations (2).

2.2 Model Updating and Iterative Learning Control of Cutting Forces

By measuring the error between simulated and actual cutting forces along the path, the coefficients can be identified by using the recursive least square (RLS) method. Write the model (1) in the following form:

$$\hat{F}(k) = \psi^T(k)\theta^* \tag{3}$$

where

$$\begin{aligned} \psi(k) &:= \left[1, X_1(k), X_2(k), X_1(k)^2, X_2(k)^2, X_1(k)X_2(k)\right]^T \\ \theta^* &:= \left[\beta_0, \beta_1, \beta_2, \beta_{11}, \beta_{22}, \beta_{12}\right]^T . \end{aligned} \tag{4}$$

When the measured cutting force, $F(k)$, and $\psi(k)$ are given for $k = 1, \cdots, N$, the optimal coefficient vector, θ^*, which minimizes $\sum_{k=1}^{N}(F(k) - \hat{F}(k))^2$, can be computed in a recursive manner as follows (e.g. [13]):

$$\begin{aligned} K(k) &= P(k-1)\psi(k)\left(I + \psi(k)^T P(k-1)\psi(k)\right)^{-1} \\ P(k) &= \left(I - K(k)\psi(k)^T\right)P(k-1) \\ \hat{\theta}(k) &= \hat{\theta}(k-1) + K(k)\left(y(k) - \psi(k)^T\hat{\theta}(k-1)\right) \end{aligned} \tag{5}$$

Since the model (1) does not include the tool and workpiece material as a determining factor, a different model must be used when a different tool or workpiece material is used. If the model is identified only by cutting tests as in [10; 11], one must either prepare a huge database for every possible combination of tool and workpiece material, or conduct a set of cutting tests every time before starting actual machining. The RLS method can be used to modify and update the model during the actual machining process. The database only provides an initial model, which is supposedly "close" to the actual process. Therefore, the size of the model database can be significantly reduced.

As was discussed in Section 1, the model-based feedforward control approach has an important advantage over feedback control approaches. On the other hand, an inherent advantage of feedback control approaches is the adaptability to unmodelled processes. In a sense, the feedforward control with iterative model updating is the combination of both approaches.

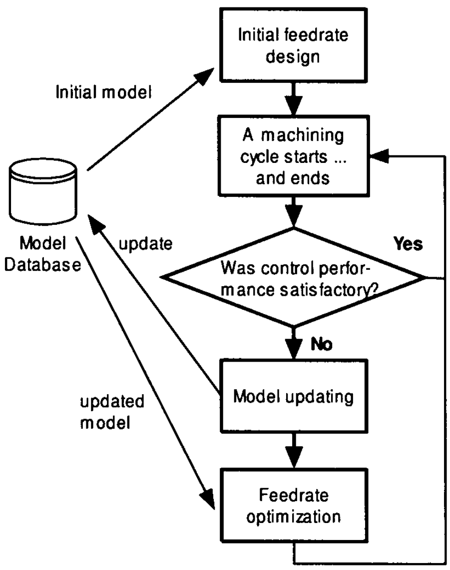


Figure 2. Overview of model-based learning control algorithm

The model-based learning control algorithm proposed in this paper is summarized as follows (see also Figure 2).

1. An initial model (1) is provided from the database. Considering the tool and workpiece material, the "closest" model in the database must be chosen.
2. Based on the initial model, the feedrate profile is computed for the first cycle such that the predicted cutting force is regulated at the given desired level.
3. The first machining cycle starts. The cutting force is measured along the path.
4. When the machining cycle is finished, the model (1) is updated by using the RLS method (5).
5. The feedrate profile is re-optimized based on the updated model.
6. Steps 3~5 are repeated until satisfactory control performance is obtained.

Although it is not possible to guarantee the convergence of this approach, it is an effective way in practice to obtain an accurate model without having a large database. The proposed method is particularly effective in cases where same (or similar) machining processes are repeated (consider manufacturing processes of parts, rather than dies or molds). The practical applicability and effectiveness of the proposed approach will be verified in case studies presented in the following section.

3 Case Studies

3.1 Cutting Force Control within Canned Cycles

Most commercial machining centers in today's market support canned cycles for drilling or tapping processes. By

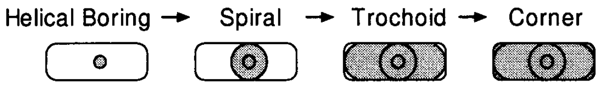


Figure 3. An example of pocketing process using canned cycles

inputting certain parameters, CL (cutter location) data to operate the machine are automatically generated by a CNC unit. The intelligent process control system for drilling and tapping processes developed by our research group [2; 3] was implemented within such canned cycles in commercially available machining centers. It was easier and more practical than to implement a process control system that works under arbitrary NC programs.

Only few commercial CNC units support canned cycles for end milling processes. However, canned milling cycles play an important role in the feature-based machining process planning [14]. The concept of feature-based machining is adopted in the STEP-NC Programming Interface proposed for the standardization in the ISO (ISO-DIS 14649) [15].

In the feature-based process planning, the entire machining process is defined as the combination of "machining features" of simple geometry (e.g. slots, pockets, and holes). Each machining feature has the geometry that can be machined by combining canned cycles. For example, as shown in Figure 3, a rectangular pocket "feature" can be machined by using the following canned cycles: 1) helical boring, 2) internal cylindrical machining by spiral cycles, 3) slotting by trochoid cycles, and 4) corner rounding.

As case studies, the control methodology proposed in the previous section is implemented within canned milling cycles, 2), 3), and 4). In today's market, such an application of cutting force control strategies is more practical as is in drilling and tapping processes.

3.2 System Configuration

Figure 4 shows an overview of the experimental setup used in the following experiments. A vertical-type machining center (VM4-II by OKK Corp.) is used. Its major specifications are: the maximum spindle speed of 20,000 rpm, the maximum rapid traverse rate of 33 m/min (X, Y, and Z axes), the maximum feedrate of 10 m/min (X, Y, and Z axes), the maximum acceleration rates of 0.67 G (X axis), 0.64 G (Y axis), and 0.56 G (Z axis), and the strokes of 630 mm (X axis), 410 mm (Y axis), and 460 mm (Z axis).

The cutting force is estimated on-line by measuring the deflection of a spindle unit by using eddy current displacement sensors (KEYENCE, EX-305). This economical estimation method of cutting forces was discussed in details by Matsubara et al. [16]. A dynamometer (Kistler Instrument Corp.'s 9272 piezoelectric four-component dynamometer) is also installed on the machine table only to evaluate the effectiveness of the proposed method. The control system only refers estimated cutting forces.

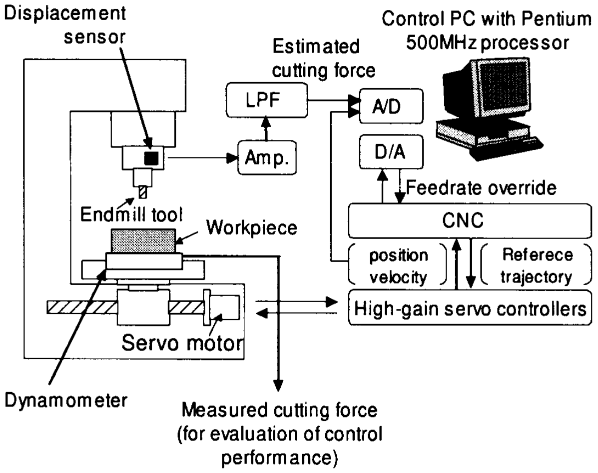


Figure 4. Overview of experimental setup

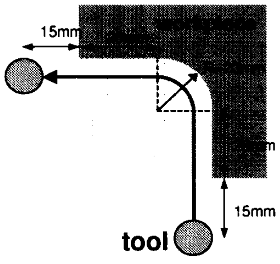
Table 1. Experimental conditions (common in all case studies)

Workpiece	
Material	Carbon steel, S50C
Tool	
Type/Material	Solid carbide end mill
Diameter	10 mm
Number of flutes	4
Tool Extension	35 mm
Cutting conditions	
Spindle speed	2800 rpm
Milling method	Downcut
Coolant	Air blow

The experimental conditions are summarized in Table 1 (common in all case studies).

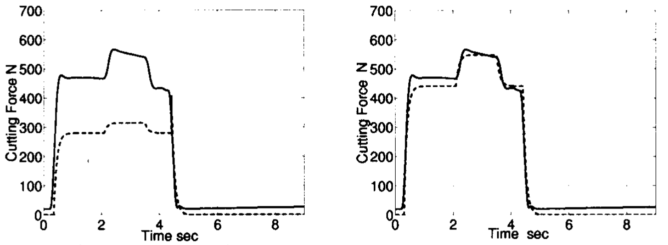
3.3 Case Study I: Cutting Force Control at Corner Rounding

The first experiment was conducted by using a corner rounding path depicted in Figure 5. Although it is a simple path, the feedrate control in such corner rounding is a practical issue. Figure 6(a-1) (solid line) shows a cutting force profile measured on the X-Y plane by a dynamometer, when the feedrate is constant at $f = 1000$ mm/min over the whole path. The sudden increase in the cutting force at the corner arc could cause the tool chipping or shorten the tool life. To avoid it, it



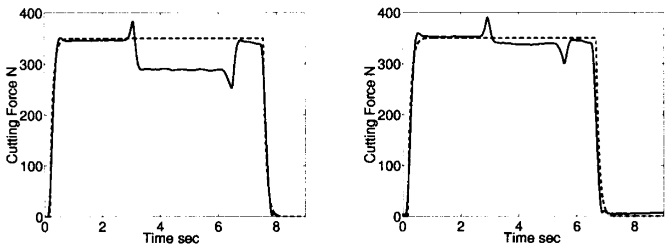
Axial depth of cut: 10 mm
Radial depth of cut: 1.5 mm

Figure 5. Tool path



(a-1) First cycle (under constant feedrate, $f = 1000$ mm/min)

(a-2) After model update



(b) Second cycle

(c) Third cycle

Figure 6. Learning cycles of feedrate optimization on the corner path, starting from the constant feedrate, $f = 1000$ mm/min (desired cutting force $= 350$ N) (solid: measured cutting force, dashed: simulated by the model).

is a common practice for an expert process planner to reduce the feedrate at corners, or more conservatively, to reduce the feedrate over the whole path, based on his/her experience. The methodology proposed in this paper gives more systematic and efficient way to optimize the feedrate.

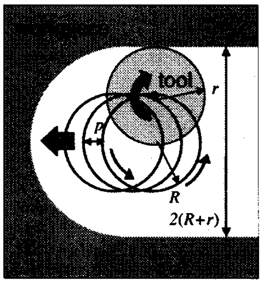


Figure 7. Slotting by trochoid cycles

Table 2. Geometry of trochoid cycles

Axial depth of cut, A_d	10.0 mm
Increment in center location per revolution, p	1.0 mm
Tool Diameter, $2r$	10.0 mm
Radius of circles, R	5.0 mm
Width of groove, $2(r+R)$	20.0 mm
Rotation direction, Q	CCW

The dashed line in Figure 6(a-1) shows a simulated cutting force by the initial model. To illustrate the effectiveness of model updating, a model of large estimation error was intentionally chosen. By comparing simulated and measured cutting force profiles, the model was updated. The estimate by the updated model is shown in Figure 6(a-2) (dashed line). Using the updated model, the feedrate profile was re-computed such that the cutting force was controlled at the constant level, $F = 350$ N, over the entire path. The same path was machined with the new feedrate profile. Figure 6(b) shows a cutting force profile in the second cycle. In the third cycle (Figure 6(c)), the error from the target level was within $\pm 5\%$ over the whole path, and the experimentation was terminated at this cycle. Although the initial model had a large estimation error, satisfactory control performance was achieved after updating the model twice.

Note that the spike-shaped errors in Figure 6(d) are caused by the transient between straight and arc parts. For the feedforward control approach, it is relatively easy to reduce such an error. By using a priori knowledge in the tool path, the control system can decelerate (or accelerate) the machine slightly earlier than the tool actually reaches the transient (see [17] for further details). For any feedback control approaches, it is generally more difficult to control such errors. Such an advantage of feedforward control approaches will be further illustrated in the following case study.

3.4 Case Study II: Cutting Force Control in Trochoid Cycles

Figure 7 illustrates a slot milling using trochoid cycles. Machining experiments were conducted on trochoid cycles of geometric parameters shown in Table 2. Compared to simple

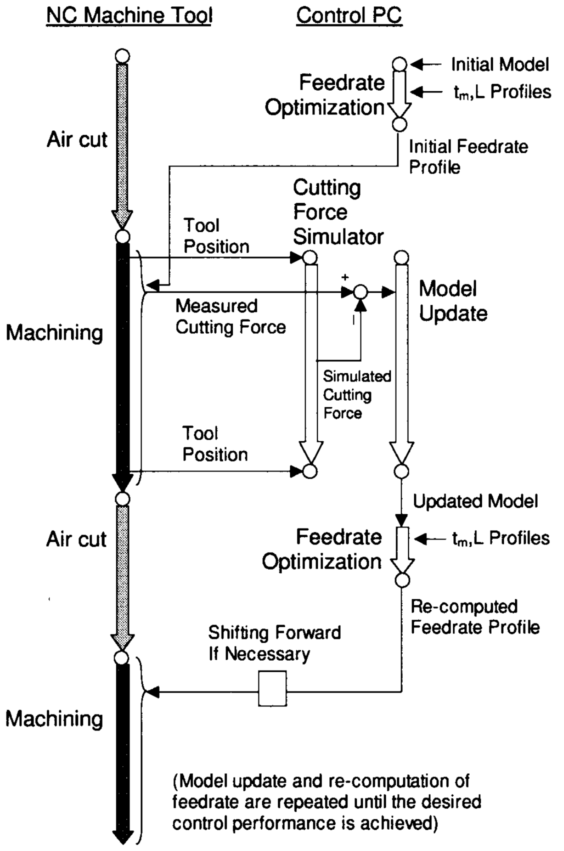
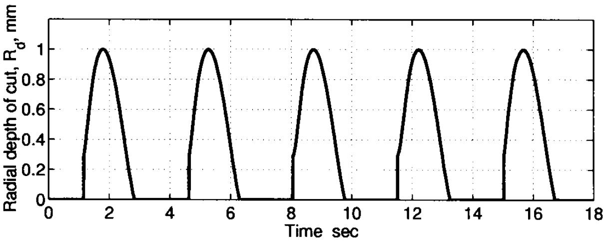
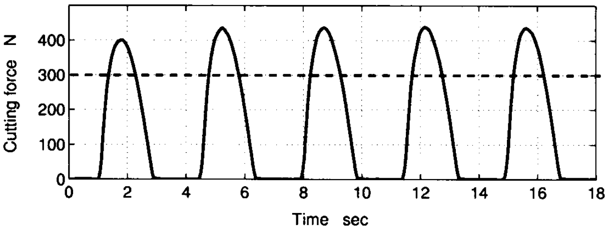


Figure 8. Timing chart of model-based learning control system of cutting forces applied to trochoid cycles



(a) Radial depth of cut, R_d



(b) Cutting force

Figure 9. Cutting force profile on the machining of a trochoid cycle under constant feedrate, $f = 560$ mm/min.

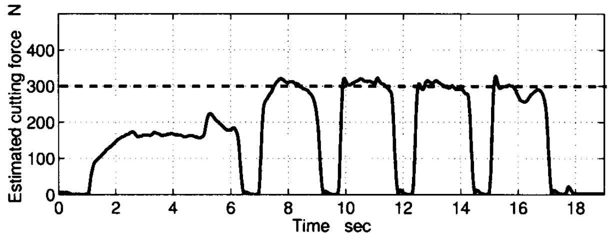
straight slotting, the trochoid path is generally subject to less cutting forces. Therefore, it is often used for harder materials. Experimental conditions are the same as shown in Table 1.

Figure 8 shows an outlined timing chart of the model-based learning control system applied to trochoid cycles. The feedrate in the initial cycle is optimized based on the initial model provided from the database. The cutting force is measured over the initial cycle and sent to the control PC. The control PC synchronously runs the cutting force simulation, and updates the model according to the error between measured and simulated cutting forces. During an air cut between the first and second cycles, the control PC re-computes the feedrate profile and sends it to the machine. The model updating and re-computation of feedrate are repeated at each cycle until the satisfactory control performance is obtained. An analogous control system can be implemented for any canned cycles.

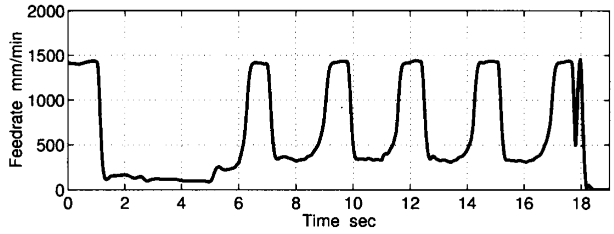
Figure 9(a) shows a simulated profile of the radial depth of cut, R_d (see Figure 1), over five trochoid cycles with the constant feedrate, $f = 560$ mm/min. Figure 9(b) shows the corresponding cutting force measured by a dynamometer. Before implementing the model-based learning control system, a feedback control system with a PI controller was tested. However, no matter how controller parameters were tuned, the feedback control system could not show satisfactory control performance. Although it was partly because our experimental setup had relatively large time delay with the external feedrate override control by the CNC unit (approximately 0.1 sec) and with signal processing on displacement sensor outputs (0.05 $\sim$ 0.1 sec), it illustrates an inherent problem with any feedback control approaches. Even if much faster override control and signal processing are possible, it is still difficult for feedback control approaches to regulate the cutting force of the change rate as fast as shown in Figure 9. It is easier to address such a problem by feedforward control approaches.

Figure 10(a) shows a cutting force profile when the learning control system overviewed in Figure 8 was activated. Figure 10(b) shows the corresponding feedrate profile. In this experiment, the target cutting force level was set at $F = 300$ N. Since the initial model had a large modelling error, the first cycle shows a relatively large error from the desired level. The model was updated during the air cut, and as a result, much better control performance was achieved on the second cycle and later.

A similar experiment was conducted to show the effectiveness of the cutting force control to enhance the productivity. In this experiment, the radius of trochoid was 15 mm, and trochoid cycles were repeated for ten times (all the other experimental conditions are the same as shown in Table 1 and 2). First, given trochoid cycles were machined under the con-



(a) Cutting force



(b) Feedrate

Figure 10. Cutting force and feedrate profiles with the learning control system activated (desired cutting force level = 300 N)

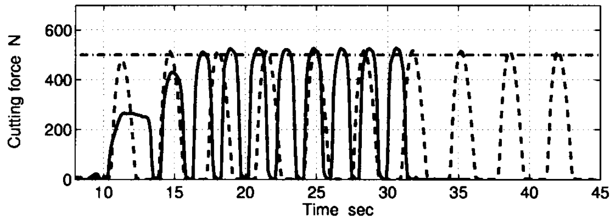


Figure 11. Cutting force profile with and without the learning control system (desired cutting force level = 500 N) (solid: with cutting force control, dashed: under constant feedrate, $f = 1120$ mm/min)

stant feedrate, $f = 1,120$ mm/min. Then, the same path was machined with the cutting force control system activated. The target cutting force level was set at $F = 500$ N, which was the maximum cutting force observed in the constant feedrate test. Figure 11 shows cutting force profiles with and without the cutting force control. When the cutting force control system is activated, the machine table is accelerated at the entry and end of each cycle, and decelerated in the middle, to regulate the cutting force at the constant level. As a result, the average machining time of each trochoid cycle (excluding the air cut) was reduced from 1.9 sec to 1.4 sec by activating the cutting force control system (about 22% reduction), while the maximum cutting force was regulated at the same level. The air cut time was also reduced when the cutting force control system was activated. The total machining time was reduced from 33 sec to 21 sec (about 35% reduction). This result illustrates the effectiveness of the cutting force control to optimize the productivity without sacrificing the tool life.

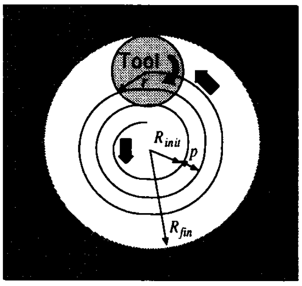


Figure 12. Internal cylindrical surface machining using spiral cycles

Table 3. Geometry of spiral cycles

Axial depth of cut, A_d	10.0 mm
Increment in radius per rotation, p	1.0 mm
Tool diameter, $2r$	10.0 mm
Initial radius, R_{init}	8.0 mm
Final radius, R_{fin}	16.0 mm
Rotation direction, Q	CCW

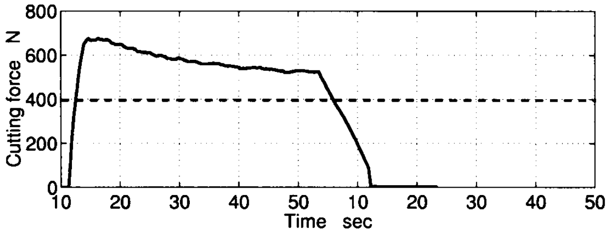
3.5 Case Study III: Cutting Force Control in Spiral Cycles

Figure 12 illustrates an internal cylindrical machining by spiral cycles. As outlined in Section 3.1, spiral cycles are typically used to expand a hole bored by an end mill or a drill. Geometric parameters of spiral cycles are shown in Table 3. Experimental conditions are the same as shown in Table 1.

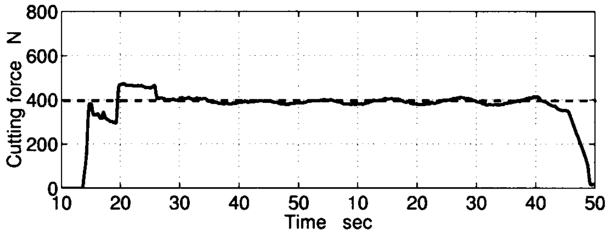
Figure 13(a) shows a cutting force profile over the entire path (total eight cycles) under the constant feedrate, $f = 1000$ mm/min. The cutting force gradually decreases as the radius of spiral increases. Figure 13(b) shows a cutting force profile when the learning control system was activated to control the cutting force at the constant level, $F_{target} = 400$ N. In spiral cycles, the model is updated and the feedrate profile is recomputed once in every rotation. In Figure 13(b), there is an error in the first and second cycles due to the modeling error in the initial model. By updating the model, however, the error from the target level became less than $\pm 5\%$ at the third cycle and later.

4 Conclusion

The feature-based process planning is widely recognized as a key strategy for the automation of machining process planning. The paper presented a cutting force control methodology applied within canned milling cycles. As a simple, but practi-



(a) Under constant feedrate, $f = 1000$ mm/min



(b) With the learning control system activated (the target cutting force level $F_{target} = 400$ N)

Figure 13. Cutting force profiles in the spiral cycle with and without the learning control system

cal example of machining by the combination of canned cycles, the machining of a rectangular pocket was presented. In particular, the following three canned cycles were considered: 1) corner rounding, 2) slot milling by trochoid cycles, and 3) internal cylindrical machining by spiral cycles.

Compared to feedback control approaches that are often found in the literature, the model-based feedforward control approach is simpler, but has an inherent advantage especially when the process is subject to quick change. This paper proposed an iterative model updating method, which allows the model-based feedforward approach to have the adaptability to unmodelled processes to some extent. Starting from the initial model provided from the database, the model is updated at each cycle, and consequently, the control law is improved in an iterative learning manner. Although the convergence of the learning process cannot be guaranteed, its practical applicability and effectiveness were verified in experimentation.

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