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Predictive Function Control for Milling Process

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Abstract

The adaptive constant control for the cutting process is an effective way to improve the productivity of the Computer Numerical Control (CNC) milling machine. This control is achieved through adjusting the feed rate online, and many scholars has been concentrated in the field. However, in of the existing adaptive constant control algorithms, the controller parameters are tuned only depends on the dynamic behavior of the controlled system, without giving effect to control the input and system output prospects. Therefore, milling force mutated because of the mutation of the depth or width of cut usually resulting in the overshooting of control system or overflow of control input. In this paper, we present a new solution to the problem, in which a mathematical model of milling process is established based on the characteristics of the CNC milling process. Then the predictive functional control law is introduced on the milling process and the controller parameters can be tuned online. The Simulation results show that the proposed method has the advantages of strong robustness to different interferences, good practicability for the milling process, and good real-time control responsibility.

Keywords*: milling process, predictive function control, nonlinear system control*

1. Introduction

The CNC machine tool is a great technological revolution in the machinery manufacturing industry. It also makes the machining automation technique a new development state. For traditional CNC machine tools, the cutting speed and feed rate is pre-determined by the programmer, and the process parameters are given in advance by the experience and knowledge of the programming technician. Once determined, these parameters cannot be changed with the transformation of the cutting conditions [1-3]. In order to meet the needs of the different cutting conditions, an adaptive control for the machine tools, is essential. The main idea in the process is that CNC can amend automatic input parameters timely according to the measured parameters and the scheduled evaluation conditions (e.g. maximum productivity, minimum processing costs , the best processing quality, etc.) or constraints (constant cutting force , constant cutting speed, constant cutting power, etc.) [4-7], so that the cutting process can work on the best state.

The model of the system has the features of variability and uncertainty because of the changeable conditions of the workpiece geometry, material characteristics, tool wear and so on. The control system performance is often seriously deteriorative, or even becomes unstable when using the conventional controller that has constant gain because of large changes of model parameters in the process. Adaptive control can automatically adjust the controller parameters when the process parameters change, so it is a possible method to handle this problem. However, the model-based adaptive controller subjects to certain restrictions in the production process because of its nonlinear, time-varying, uncertainties and non-minimum phase characteristics of the model [8-10].

In this paper, a process control model is established aiming at the above-mentioned characteristics of the CNC milling and on its operating parameters. Based on this model, a predictive functional controller is designed to realize f the optimal calculation for the real-time control, so as to solve the problem of the overshooting of the system output or the excessive control input when the milling force mutations are induced by the cut depth and width, or by the parameters of mutations [11-12].

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The rest of the paper is organized as the Model of the Milling Process in section 2; the Proposed Predictive Function Control Method in section 3; Simulation Results and Discussion in section 4, and followed by Conclusions in section 5.

2. The Model of the Milling Process

The processing system is shown in Figure 1. It consists of the servo mechanism, the cutting process, the detection devices and etc.

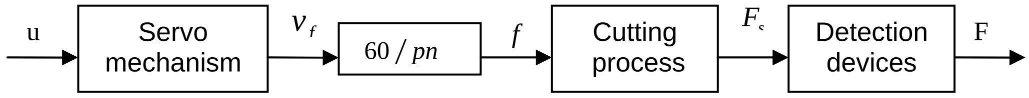

Figure 1. Processing Model

The servo link can be expressed by a second - order system,

$$v_f = \frac{K_n \omega_n^2}{s^2 + 2\xi\omega_n s + \omega_n^2} u \tag{1}$$

Where, s is the plural of the complex domain of the continuous system, and also is the Laplace transform operator. v_f is the feed rate(mm/s); u is the servo input(V); K_n is the servo gain; ω_n is the natural frequency of the servo system(rad/s); ξ is the damping coefficient, *f* is the feed rate (mm/r) and can be expressed as:

$$f = \frac{60}{pn} v_f \tag{2}$$

Where, n is the spindle speed(r/min); p is the frequency of the tool in the milling, in turning and drilling, p = 1. Static cutting force can be defined as:

$$F_s = K_s a f^m = (K_s a f^{m-1}) f \tag{3}$$

Where, K_s is the (N/mm^2), m is the index (usually m<1), F_S and m depend on the workpiece material and tool shape; a is the back engagement of the cutting edge (mm).

According to the different characteristics of the processes, the dynamic process of F_n can also be expressed by Equation (3). Assume that m = 1; then the dynamic process of F_n can be indicated by a first-order process,

$$\frac{F_s(s)}{f(s)} = \frac{K_s a}{\tau s + 1} \tag{4}$$

Where, τ is the time constant. Through the measurement of sensor, F can be measured and the cutting force can be expressed as,

$$F = K_e F_s \tag{5}$$

Where, K_e is the conversion factor of the dynamometer. Its dynamic process is then expressed as,

$$F = \frac{K_e}{\tau_e s + 1} F_s \tag{6}$$

Where, τ_e is the time constant of the dynamometer response. Under normal circumstances, the response of the dynamometer and other electronic equipment is very fast comparing the process, and therefore the cutting force can be expressed by Equation (5).

Based on the above analysis, the parameters are different for different processes, so the corresponding models are also different. Nevertheless, the sampling time might be different even if in the same process and it willresult in different discrete models. Figure 2 shows the model obtained by Equations (1), (3) and (5) ; and we get:

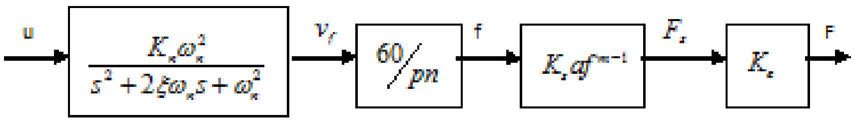

Figure 2. Process Mathematics Model

$$\frac{F(s)}{u(s)} = \frac{K\omega_n^2}{s^2 + 2\xi\omega_n s + \omega_n^2} \tag{7}$$

Where, K is the overall gain of the processing. It can be expressed as,

$$K = 60K_n K_s K_e af^{m-1}/(pn) \tag{8}$$

From Equation (8), it can be seen that the gain K of the model changes with the back of cut, spindle speed and feed rate. In addition, the process can also be changed to the first order inertia link with a time delay:

$$\frac{F(s)}{u(s)} = \frac{K}{T_1 s + 1} e^{-\tau s}$$

Where, K is the process gain; T_1 is the time coefficient of process. Both K and T_1 are the function of the back engagement of the cutting edge. The Equation (8) can also be considered as the fitting when the damping of the second-order system is very large in Equation (7).

The actual process model is much more complex; and it cannot even be represented by the appropriate mathematical expressions. In addition, there are other variation factors in the actual system, such as the clearance of the mechanical drive, the component insensitives and the output saturation.

The real process system consists of multiple dynamic links, and belongs to the higher order dynamic system. However, in order to facilitate the research, the real processing system is simplified into a low-level model, and the process tends to be linear. This is typically a very rough approximation. In addition, the processing model has some inaccuracy and uncertainty because of the limited understanding of the process. Furthermore, there are the measurement uncertainty, the accuracy of the regression, the material inequality, the voltage/load changes and the environmental factors, which must be considered in the controller design

3. The Proposed Predictive Function Control Method

As shown in Figure 3, the constant control system consists of the controller and the plant (the milling process) in milling processing, where the servo feed and milling connected in series constitutes the milling process. In Figure 3, u is the servo input, v_f the feed rate, F the actual milling force, and F_r the reference milling force.

The forecasting model of the milling process for the prediction function controller is selected as,

$$\frac{F(s)}{u(s)} = \frac{K}{T_1 s + 1} e^{-\tau s} \quad (9)$$

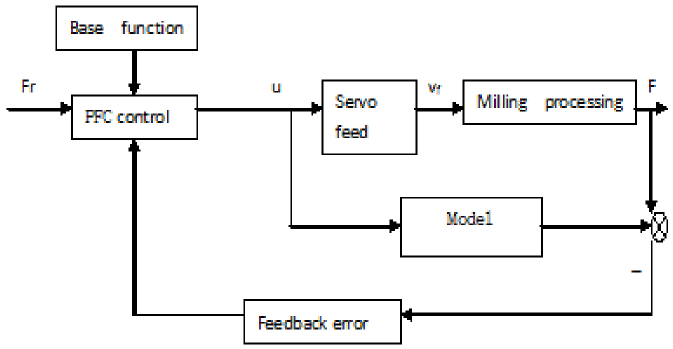

Figure 3. Constant Control System in Milling Processing

In the predictive functional control algorithm, the control accuracy depends on the choice of the basis function. Usually the step function and ramp function will be able to meet the requirements. For a step change in the first order of objects and settings, simply a basis function is selected; that is the step function. When the settings changes to that including the ramp signal, two basis functions should be chosen, which would consist of the step function and ramp function. When the variation of the setting charged with an interval which is less than or equal to a certain threshold, the control input can take a basis function [7], which is the step function. When the variation of setting in the charged interval is greater than a certain threshold, the control input can take two basic functions, which is the step function and ramp function. When using a basis function, that is a step function,

$$u(k+i) = u(k) \quad i = 1, \quad 2, \quad \cdots \quad P-1 \quad (10)$$

To get the control law of the system of the first order plus the time delay, first consider T_d=0, adding the discretization of a zero-order hold, differential equations of the model can be obtained as:

$$F_m(k+1) = \alpha_m F_m(k) + K(1-\alpha_m)u(k)$$
(11)

Where, $\alpha_m = e^{(-T_S/T_1)}$ According to the formulas (10) and (11), following equation can be obtained:

$$F_m(k+P) = \alpha_m^P F_m(k) + K(1-\alpha_m^P)u(k) \quad (12)$$

Now, we need to optimize the objective function:

$$J_P = \min\left(\sum_{i=P_1}^{P_2} \left[F_r(k+i) - F_P(k+i)\right]^2\right)$$

$$F_P(k+i) = F_m(k+i) + e(k+i)$$

Where, P_1 and P_2 are the lower and upper limits of the optimizion time domain, $F_P(k+i)$ is the prediction of process output, $F_m(k+i)$ is the model output at time $k+i$, $e(k+i)$ is the future error.

Take P_1=P_2=P, and to make:

$$\frac{\partial J_P}{\partial u(k)} = 0 \quad (13)$$

The amount of control at time k is:

$$u(k) = \frac{F_r(k+P) - \beta^P F_r(k) - F(k)(1-\beta^P)}{K(1-\alpha_m^P)} + \frac{F_m(k)}{K} \quad (14)$$

When $T_d \neq 0$, referring to Smith predictor control theory, the PFC still uses the model of $T_d = 0$,
but it needs to amend the system object output.
Let $D = T_d / T_s$, the specific amendment such as the formula (15) shows.

$$F_{Pav}(k) = F(k) + F_m(k) - F_m(k-D) \quad (15)$$

$y_{Pav}(k)$ is the output value for the revised process, then the formula (8) can be amended to:

$$e(k+i) = F_{pav}(k) - F_m(k) \quad (16)$$

Substitute $F(k)$ with $F_{pav}(k)$ in formula (14), we obtain the output of PFCin the first order plus pure lag as.

$$u(k) = \frac{F_r(k+P) - \beta^P F_r(k) - F_{pav}(k)(1-\beta^P)}{K(1-\alpha_m^P)} + \frac{F_m(k)}{K} \quad (17)$$

4. Simulation Results and Discussion

Difine the model parameters in the milling process as follows: when the spindle speed is 550r/min, the damping coefficient $\xi = 0.6$, natural frequency $\omega_n = 2.89 rad.s^{-1}$, and the process gain $K = 142N.V^{-1}$. If the zero-order hold is applied, the discrete model of the formula (7) can be expressed as.

$$G(z) = \frac{F(z)}{u(z)} = \frac{b_1 z + b_0}{z^2 + a_1 z + a_0} \quad (18)$$

Where, a_1, a_0, b_1 and b_0 are the coefficients of z transform (from continuous systems to discrete systems).

Take the sampling period T=0.5s, different back engagements of cutting edge are shown in Table 1. In the first stage, a=2.54; the second, a=1.91; the third, a=3.81.

Table 1. Model Parameter of Milling Process

back engagement of cutting edge (mm)	damp coefficient	natural frequency(rad/s)	process gain
2.54	0.6	2.89	142
1.91	0.1	2.3	128
3.81	0.9	2.97	306

The simulation results in different back engagement of cutting edge are shown in Figure 4.

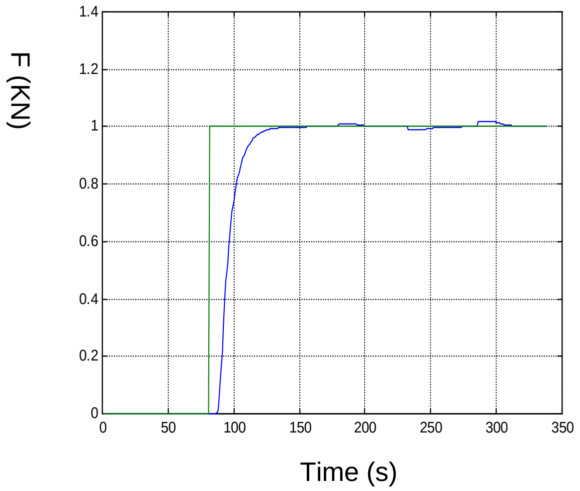

Figure 4. The Cutting Force Simulation of a Different Back Engagement of Cutting Edge

From Figure 4, we observe that a steady value is 1KN, and F is 1.01KN in the first stage when the time is 180s and a is 2.54. F is 0.98KN in the second stage when the time is 230s and a is 1.91. F is 1.03KN in the third stage when the time is 280s a is 3.81. We also observe that the system can adjust the noise response to the steady value quickly. The simulation results show the method has the advantages of strong anti-interference ability, strong robustness, good practicability; and its adjustment responses can meet the real-time control requirements.

5. Conclusion

In this paper, the predictive functional control algorithm is proposed to the CNC milling process.

(1) The algorithm is designed on the the influences of the system input and output, so the stability and the output performance of the predictive functional control are greatly improved while keeping the algorithm simple.
(2) The algorithm is on the prediction function control law of the milling process, which can meet the real - time requirements of CNC milling constant control.
(3) The predictive functional control for the characteristics of the CNC milling process has strong robustness and anti-interference ability. It is suitable for the time-varying process and can significantly improve the output performance of the controlled system.

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