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Proceedings of the 72nd World Foundry Congress
21-25th May 2016, Nagoya, Japan

Flow Rate Control of Automatic Pouring Machine by Iterative Learning Control

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This paper presents pouring flow rate control of the automatic pouring machine by iterative learning control. Pouring process has a feature of repeating motion of ladle tilting. So, iterative learning control is applied to pouring flow rate control. Iterative control systems can be viewed as 2D systems because systems have two kinds of dynamics: the one along time direction for each repetition index, and the one with respects to the repetition index. Therefore the iterative learning control system was designed by 2D control theorem. In this research, the motor attached to the ladle is controlled by output feedback based iterative learning control for flow rate control. The learning controller depends on the information of the input and the tracking error in both the present iteration and a finite number of previous iterations. A target angular velocity is calculated from a target flow rate by inverse model of pouring model. The output was able to be matched to the target angular velocity by a few times of repeating trial.

Keywords: *Automatic pouring machine, Flow rate control*

1. Introduction

In pouring process, molten metal is poured into the mold repeatedly. And the angle of ladle can be calculated from the desired flow rate. So we propose that the angle of the ladle is controlled by iterative learning control. Iterative learning control is a method to track the output of the dynamic system to the desired trajectory by modifying the input based on the trial error. The purpose of this paper is to apply iterative learning control to flow rate control of the automatic pouring machine.

2. Automatic pouring machine

Fig.1 shows the outline of the automatic pouring machine. The DC motor revolves the ladle, and its rotation angle is measured by the encoder. The weight of the liquid in the ladle is measured by the load cell. The microcontroller is used for signal sending and receiving with the PC, the DC motor and the load cell.

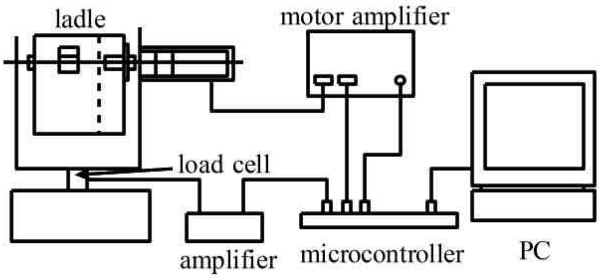

Fig. 1 Automatic pouring machine

3. Model following learning control

It's supposed that the automatic pouring machine is modeled by the discrete time system as follows.

$$\begin{aligned} x(t+1) &= Ax(t) + Bu(t) \\ y(t) &= Cx(t) + Du(t) \end{aligned} \tag{1}$$

where $\boldsymbol{x(t)}, \boldsymbol{u(t)}, \boldsymbol{y(t)}$ are the state, the control input and output respectively. And $\boldsymbol{t}$ is the time step. The following discrete time model system is considered as the model that outputs the target value that this controlled system should follow.

$$\begin{aligned} x_m(t+1) &= A_m x_m(t) + B_m r(t) \\ y_m(t) &= C_m x_m(t) + D_m r(t) \end{aligned} \tag{2}$$

where $x_m(t), r_m(t), y_m(t)$ are the state, the control input and output of the model system respectively.

The model following learning control that proposes by this research is considered as follows. We suppose that the system (1), the model system (2), initial conditions $x(0) = x_0$, $x_m(0) = x_{m0}$ and reference input $\{r(t), t = 0,1,\cdots,N\}$ are given. The objective is to design a controller such that the output $y(t)$ of (1) tracks the step response $y_m(t)$ of the model system (2). To achieve this objective the trial errors $\mathrm{y_m} - y(t)$ and the inputs the used in each trial are memorized. The inputs are modified based on the errors and the previous inputs to reduce the tracking error. After some repetitions the appropriate inputs are obtained and the outputs converge to the output of the model system.

When considering the model following learning control as mentioned above, the control system has two kinds of independent dynamics: the one along time direction for each repetition index, and the one with respects to the repetition index.Then the system (1) and the model system

(2) can be viewd as 2D discrete systems in the form

$$\begin{aligned} x(k,t+1) &= Ax(k,t) + Bu(k,t) \\ y(k,t) &= Cx(k,t) + Du(k,t) \end{aligned} \qquad (3)$$

$$\begin{aligned} x_m(k,t+1) &= A_m x_m(k,t) + B_m r(t) \\ y_m(k,t) &= C_m x_m(k,t) + D_m r(t) \end{aligned} \qquad (4)$$

where $x(k,t)$, $y(k,t)$, $u(k,t)$, $x_m(k,t)$, $y_m(k,t)$ are state, output and control input of the system, state and output of the model system espectively. And the tracking error of the k-th iteratin is defined as follow.

$$e(k,t) = y_m(k,t) - y(k,t) \qquad (5)$$

Let $\Delta u(k,t)$ be the modification of control input of the k-th iteration, the general learning control law is expressed in the following.

$$u(k+1,t) = u(k,t) + \Delta u(k,t) \qquad (6)$$

Now define

$$\begin{aligned} \eta(k+1,t) &= x(k+1,t) - x(k,t) \\ \eta_m(k+1,t) &= x_m(k+1,t) - x_m(k,t) \end{aligned} \qquad (7)$$

Then (3)-(7) can be rewriten as

$$\begin{bmatrix} \eta(k+1,t+1) \\ \eta_m(k+1,t+1) \end{bmatrix} = \begin{bmatrix} A & 0 \\ 0 & A_m \end{bmatrix} \begin{bmatrix} \eta(k+1,t) \\ \eta_m(k+1,t) \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} \Delta u(t) \qquad (8)$$

$$e(k+1,t) = \begin{bmatrix} -C & C_m \end{bmatrix} \begin{bmatrix} \eta(k+1,t) \\ \eta_m(k+1,t) \end{bmatrix} - D\Delta u(t) + e(k,t)$$

The controller that the traking error is converge to a zero after some repetitions is given by

$$\Delta u(k,t) = K_1 \begin{bmatrix} \eta(k+1,t) \\ \eta_m(k+1,t) \end{bmatrix} + K_2 e(k-1,t) \qquad (9)$$

where K_1 and K_2 are given by the following equation [1].

$$\begin{bmatrix} K_1 & K_2 \end{bmatrix} = NY^{-1} \qquad (10)$$

Symmetric matrices $Y > 0$ and $Z > 0$ can be determined by satisfying the LMI

$$\begin{bmatrix} Z - Y & 0 & Y\hat{A}_1^T + N^T\hat{B}_1^T \\ 0 & -Z & Y\hat{A}_2^T + N^T\hat{B}_2^T \\ \hat{A}_1 Y + \hat{B}_1 N & \hat{A}_2 Y + \hat{B}_2 N & -Y \end{bmatrix} < 0 \qquad (11)$$

where

$$\hat{A}_1 = \begin{bmatrix} A & 0 & 0 \\ 0 & A_m & 0 \\ 0 & 0 & 0 \end{bmatrix}, \hat{A}_2 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ -C & C_m & I \end{bmatrix}$$

$$\hat{B}_1 = \begin{bmatrix} B \\ 0 \\ 0 \end{bmatrix}, \hat{B}_2 = \begin{bmatrix} 0 \\ 0 \\ -D \end{bmatrix}$$

4. Simulation

We considered the angle of the ladle follows in the target angle which doesn't include the natural frequency of the liquid level to suppress shaking of molten metal in the ladle when a ladle revolves. So the model system includes the notch filter that suppresses shaking of the liquid level.

Simulation result is shown in Fig. 2 and Fig. 3. Rotation angle follows the output of the model system by an approximately 1st iteration.

5. Conclusion

Rotation angle of ladle can track to the output of the model system by using the model following learning control.

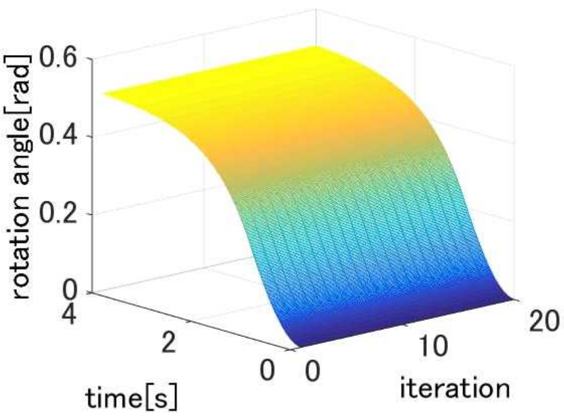

Fig. 2 Rotation angle of ladle

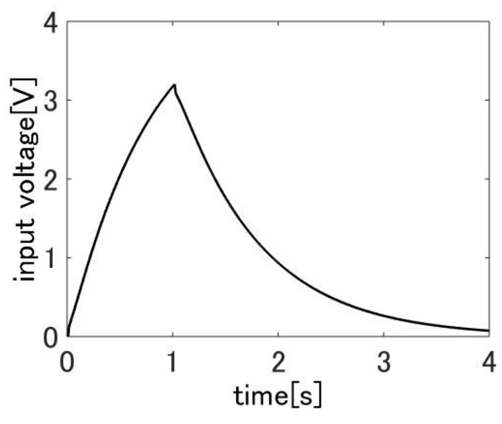

Fig. 3 Input voltage to the motor

References

[1] K. Gakowski, Eric Rogers, S. Xu, J. Lam, and D. H. Owens, "LMIs – a fundamental tool in analysis and controller design for discrete linear repetitive processes", IEEE Transactions on Circuits and Systems I: Fundamental Theory and Applications, No.49(6) pp.768-778 (2002).