Nonlinear Internal Model Controller based on Local Linear Models, and its Application

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Abstract

In this paper, nonlinear internal model controller based on local linear models, and its Application. The internal model control has a simple structure and has a high robustness for system uncertainties. However, there are few studies of internal model control schemes for nonlinear systems. On the other hand, many controlled systems have the nonlinearity. The effectiveness of the newly proposed control scheme is numerically evaluated on experiment examples in comparison with the conventional control methods for nonlinear systems.

Keywords: Control, . Local Linear Models, Internal Model Controller

1. Introduction

In recent years, with the development of computer technology, design methods for control systems with higher-order compensators have been considered with the aim of improving control performance [1]. In particular, it is difficult to obtain a desirable control response with a simple controller using fixed parameters because the characteristics of the system change significantly due to changes in the system with non-linearity, operating conditions, and changes in the environment.

On the other hand, a model-driven control method [2] has been proposed in which the controlled object is described by the most detailed mathematical formula and the model of the controlled object is incorporated into the control system. Internal model control (IMC) is one of the model-driven control methods [2,3]. IMC is characterized by a simple control system structure and high robust stability against uncertainty of the controlled object. However, there are few examples of applying IMC to nonlinear systems. For example, data-driven IMC that uses a database to extract data similar to the current data as a neighborhood and control it according to the required point. Systems have been proposed, but these methods require enormous amounts of time for computational processing [4].

By the way, the authors have previously proposed a method for calculating control parameters using the concept of the local linear model method [5]. In this method, multiple local linear models can be constructed for a nonlinear system, system parameters corresponding to each local linear model can be obtained, and weights can be applied to design a control system. For nonlinear systems. It is possible to control with fast calculation processing.

Therefore, in this paper, as a method of designing an internal model for a nonlinear system, we propose a method of designing a control system by individually calculating the system parameters corresponding to each local linear model and weighting them. In this method, the system parameters are determined for the local linear model divided into multiple parts, so it can be expected that more appropriate tuning can be performed for the nonlinear system. Since it is not necessary to build the database required by the data-driven IMC system, the time required for construction can be reduced. As a result, the load and processing time can be significantly reduced in terms of memory capacity and calculation time.

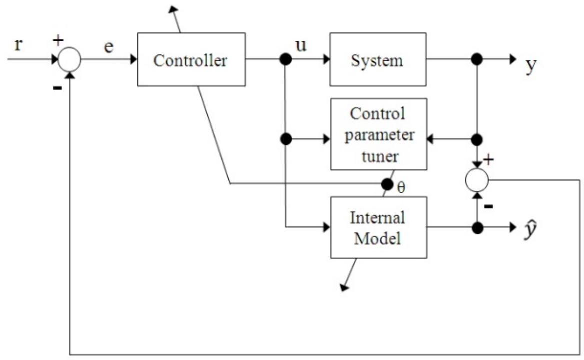

Fig. 1. Block diagram of the proposed method

2. IMC design using a local linear model

In this paper, we construct a local linear model around the equilibrium point that differs depending on the characteristics of the static characteristics of the nonlinear model. Calculate the control parameters corresponding to each local linear model and obtain the estimated value of the system output. Then, the non-linear control is realized by calculating the distance between the actual system output and the estimated value and adjusting the load of the system parameters according to the distance. Fig.1 shows the block diagram of the proposed control system.

2.1. *System description*

First, it is assumed that the system dealt with in this paper is given by the following equation.

$$y(t) = f(\varphi(t-1)) \quad (1)$$

where, $y(t)$ represents the system output and $f(\cdot)$ represents the nonlinear function. In addition, $\varphi(t-1)$ represents the state (historical data) before the time $t-1$ of the system, and is called an information vector. The information vector $\varphi(t-1)$ is defined by the following equation.

$$\varphi(t-1) := [y(t-1),\ y(t-2), \cdots, y(t-n_y) \quad u(t-1), u(t-2), \cdots, u(t-n_u)\ ] \quad (2)$$

Furthermore, $u(t)$ is the control input, and n_y and n_u are the output and input orders, respectively. Now, suppose that the nonlinear system represented by Eq. (1) can be locally represented by a linear model like the following Eq.

$$A(z^{-1})y(t) = z^{-(k_m+1)}B(z^{-1})u(t) \quad (3)$$

where, z^{-1} represents a time-delayed operator that means $z^{-1}y(t) = y(t-1)$. In addition, k_m represents the minimum estimate of wasted time. In many process systems represented by chemical processes, it is often impossible to clearly specify the dead time. Therefore, if the dead time is known, set k_m to that value, and if the range of dead time is unknown, set $k_m = 0$.

In addition, $A(z^{-1})$ and $B(z^{-1})$ are given by the following equations.

$$A(z^{-1}) = 1 + a_1 z^{-1} + \cdots + a_{n_y} z^{-n_y} \quad (4)$$

$$B(z^{-1}) = b_0 + b_1 z^{-1} + \cdots + b_{n_u} z^{-n_u} \quad (5)$$

where, if the dead time is unknown or ambiguous, the insufficient dead time information is supplemented by securing the order of $B(z^{-1})$ in n_u dimensions.

2.2. *Designing an internal model controller using a local linear model*

In this paper, we consider the control law (IMC) of the following Eq.

$$u(t) = Q(z^{-1})e(t) \quad (6)$$

$$Q(z^{-1}) = \frac{A(z^{-1})}{B(1)}\left(\frac{1-\lambda}{1-\lambda z^{-1}}\right)^n \quad (7)$$

where, λ is the design parameter of the filter used in the range of $0 \leq \lambda < 1$, and n is the order of the filter. In addition, by using $B(1)$, even if $B(z^{-1})$ contains an unstable zero point (non-minimum phase system), it can be dealt with because pole-zero cancellation is avoided.

In addition, $e(t)$ is a control error signal and can be defined as follows with $r(t)$ as the target value.

$$e(t) := r(t) - \{y(t) - \hat{y}(t)\} \quad (8)$$

where, $\hat{y}(t)$ is the internal model output and is shown by the following Eq.

$$\hat{y}(t) = -A(z^{-1})y(t) + z^{-(k_m+1)}B(z^{-1})u(t) \quad (9)$$

Since many real systems have non-linearity, it is difficult to always obtain good control results when the system parameters are fixed. Therefore, in this method, the system parameters included in equations (4) and (5) are self-adjusted according to the characteristics of the system based on the local linear model, so they are replaced as follows.

$$\hat{A}(z^{-1}:t) = 1 + \hat{a}_1(t)z^{-1} + \cdots + \hat{a}_{n_y}(t)z^{-n_y} \quad (10)$$

$$\hat{B}(z^{-1}:t) = \hat{b}_0(t) + \hat{b}_1(t)z^{-1} + \cdots + \hat{b}_{n_u}(t)z^{-n_u} \quad (11)$$

where, $\hat{A}(z^{-1}:t)$ and $\hat{B}(z^{-1}:t)$ represent the control target at time t, and the above assumptions are inherited. Also, n_y is the order of the output. Along with this, equations (7) and (9) are described as the following Eq.

$$Q(z^{-1}:t) = \frac{\hat{A}(z^{-1}:t)}{\hat{B}(1:t)}\left(\frac{1-\lambda}{1-\lambda z^{-1}}\right)^n \quad (12)$$

$$\hat{y}(t) = -A(z^{-1}:t)y(t) + z^{-(k_m+1)}B(z^{-1}:t)u(t) \quad (13)$$

After the above preparations, design an internal model controller using a local linear model. The specific algorithm is summarized below.

[STEP1] Construction of multiple linear models

For the nonlinear model, multiple linear models are constructed, the system is identified by the collective least squares method, and the parameters of $A(z^{-1})$ and $B(z^{-1})$ included in the linear model of the following equation are estimated.

$$A_i(z^{-1})y(t) = z^{-(k_m+1)}B_i(z^{-1})u(t) \quad (i = 1,2,\cdots,N) \quad (14)$$

where, N represents the number of divisions of the local linear model, and $i = 1,2,\cdots,N$ or less Unless otherwise specified, i takes these values. In addition, $A_i(z^{-1})$ and $B_i(z^{-1})$ are given by the following equations.

$$A_i(z^{-1}) = 1 + a_{i,1}z^{-1} + \cdots + a_{i,n_y}z^{-n_y} \quad (15)$$

$$B_i(z^{-1}) = b_{i,0,} + b_{i,1}z^{-1} + \cdots + b_{i,n_u}z^{-n_u} \quad (16)$$

[STEP2] Weight calculation

Next, for each local linear data calculated in [STEP1], the estimation error $\epsilon_i(t)$ is calculated for each model, and the weight ω_i is calculated based on this. $\epsilon_i(t)$ is the error between the system output value y(t) and the estimated output value $\tilde{y}_i(t)$ of each linear model. Here, $\tilde{y}_i(t)$ is calculated by the following equation based on equation (14).

$$\tilde{y}_i(t) = -A_i(z^{-1})y(t) + z^{-(k_m+1)}B_i(z^{-1})u(t) \quad (17)$$

where, $A_i(z^{-1})$ and $B_i(z^{-1})$ use the system parameters of each linear model estimated in [STEP1].

$$\epsilon_i(t) = |y(t) - \hat{y}_i(t)| \quad (18)$$

$$\omega_i(t) = \frac{1/\epsilon_i(t)}{\sum_{i=1}^{N} 1/\epsilon_i(t)} \quad (19)$$

Fig. 2. Process system

Furthermore, $\omega_i(t)$ is the weight corresponding to the selected i-th information vector. The smaller the difference between the output value of the actual system and each linear model, the larger this weight becomes. Note that the following equation is satisfied when $\omega_i(t)$ is calculated based on equation (19).

$$\sum_{i=1}^{N} \omega_i(t) = 1 \quad (20)$$

[STEP3] Determining system parameters

Using the weights obtained in [STEP2] and$A_i(z^{-1})$ and $B_i(z^{-1})$ in Eqs. (15) and (16), the system parameters are calculated by the following equation.

$$\hat{A}(z^{-1}:t) = \sum_{i=1}^{N} \omega_i A_i(z^{-1}) \quad (21)$$

$$\hat{B}(z^{-1}:t) = \sum_{i=1}^{N} \omega_i B_i(z^{-1}) \quad (22)$$

With this system parameter, equations (10) and (11) are updated to obtain the output $\hat{y}(t)$ of the local linear model.

3. Experimental example

The effectiveness of the proposed method will be examined through application to the thermal process system shown in Fig.2. This system uses an incandescent light bulb (40W) as the control target, and controls the surface temperature of the light bulb by changing the voltage applied to the light bulb by controlling the Joule heat of the filament. A heat transfer pair (R52-CA10AE) sensor is attached to the top of the light bulb. Also, measure the temperature of the light bulb with a thermocouple. Furthermore, the temperature of the thermocouple is converted into a voltage by the thermocouple conversion IC, and after A/D conversion, the data is output to the computer. The control input is calculated using the output data.

A PWM signal with a duty ratio according to the control input is output through D/A conversion, and a current flows through the heater by a solid state relay (SSR).

Therefore, the control input $u(t)$ in this experiment is the duty ratio (0 to 100%) of the PWM signal given to the SSR, and the control output $y(t)$ is the temperature of the surface of the light bulb.

First, the target value $r(t)$ is given as follows.

$$r(t) = \begin{cases} 50(0 \le t < 50) \\ 70(50 \le t < 100) \\ 100(100 \le t < 150) \\ 130(150 \le t < 200) \end{cases} \tag{23}$$

Next, a local linear model is constructed in the control input range shown below. The number of divisions was N=2.

$$\begin{cases} 0 \le u_1 < 30 \\ 20 \le u_2 < 100 \end{cases} \tag{24}$$

Here, the input / output data in the range of u is saved as the initial database. In Eq. (24), there is a place where the area of u overlaps, but this avoids that a good response cannot be obtained by selecting the database when the request point is selected near the division of each database. It is provided for this purpose. The values of various design parameters included in the proposed method are $n_y = 2, n_y = 2$, and $k_m = 0$. Furthermore, the parameters of IMC are $\lambda = 0.5$ and $n = 1$. Here, λ was designed to have the desired rising characteristics.

First, for comparison with the conventional method, the fixed PID control method widely used in the industry is applied. However, for the PID parameter, the value calculated based on the CHR method is used. Its PID parameters are shown below.

$$K_P = 3.66, K_I = 0.38, K_D = 5.98 \tag{25}$$

First, Fig.3 shows the control results of the fixed PID method and the control results of the proposed method. In addition, Fig.4 shows the temporal change of the weight by the proposed method in this case. From the results in Fig.3 and Fig.4, it can be seen that the weight of the proposed method changes according to the characteristics of the system, and the responsiveness is greatly improved.

4. Conclusion

In this paper, we proposed a new design method for an IMC system that constructs multiple local linear models for a nonlinear system and adjusts the system parameters corresponding to them. As a result, it was verified through experiments that the system parameters were adjusted appropriately according to the characteristics of the system and good control results could be obtained. In the future, we plan to study the method of dividing the local linear model of this method.

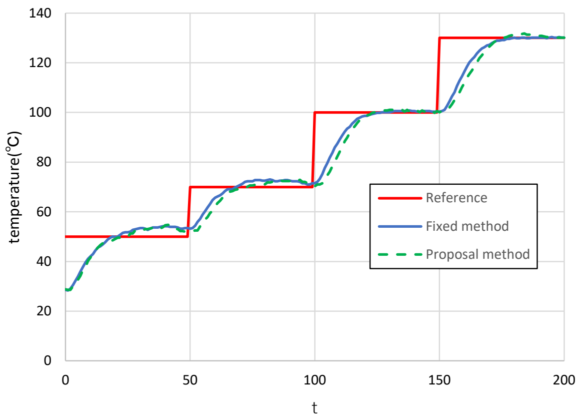

Fig. 3. Experimental result

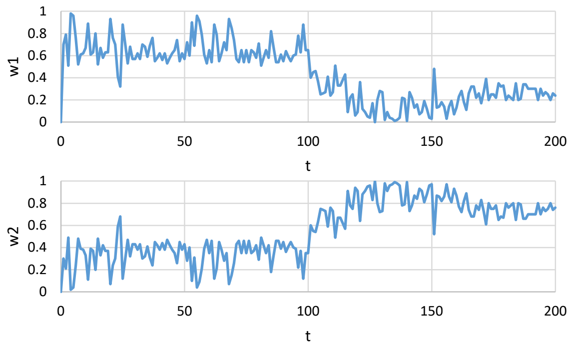

Fig. 4. Change in weight

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