Design of a Data-oriented 2DOF Nonlinear Controller

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***Abstract*— This study considers about the 2 degree-of-freedom (2DOF) nonlinear controller. The proportional-integral-derivative (PID) controllers have been widely used in many process systems. There are broadly-divided two design methods. One is a model-based controller design that tunes PID parameters based on a system model. The other is a data-oriented controller design that tunes these parameters by using obtained experimental data. Model-based controller design schemes are effective for designing a robust controller. On the other hand, data-oriented control design scheme can design a controller with a high regard for tracking property. In this research, a hybrid data-oriented 2DOF nonlinear controller is proposed. According to the scheme, a robust closed-loop control system is first constructed by prior information of a system. Then, a set of experimental data is obtained by the closed-loop system, and a constructed feedforward cerebellar model articulation controller based proportional-derivative (CMAC-PD) compensator is learned by using the data in an offline manner. The method can guarantee a robustness of the closed-loop system, and the CMAC-PD compensator can absorb nonlinearity of a system. The effectiveness of the proposed control system is evaluated by a simulation example.**

I. INTRODUCTION

The proportional-integral-derivative (PID) controller [1], [2], [3] has been applied in many process systems, including chemical and petroleum processes because its control structure is simple and the meaning of the PID parameters is clear. Controller design schemes are broadly divided into two categories: (i) Model-based controller design that is based on a system model of a controlled object design and (ii) data-oriented controller designs that uses I/O data of a closed-loop system directly for its controller design. A robust controller design [4] has been established as one of model-based controller design schemes. In the robust controller design scheme, it treats a difference between a real system and a mathematical model as an uncertainty when prior information of a system is little, and it is explicitly-considered in a controller design. However, the robust controller design scheme is a conservative controller design scheme in order to guarantee a robustness of a closed-loop system, thus it sacrifices its tracking property to a reference signal. Especially, it is necessary to liberally estimate a uncertainty, therefore it strongly affects the tracking property of a closed-loop system. On the other hand, a data-oriented controller design scheme typified by fictitious reference iterative tuning (FRIT) [5], [6], [7] determines control parameters in order to adjust a closed-loop transfer characteristic to a desired transfer characteristic by just using experimental data. Data-oriented controllers have attracted attention with a central focus on industrial fields because these design methods can reduce design costs of a system model. The data-oriented controller design scheme can be treated as one of aggressive design schemes with a focus on its tracking property. Therefore, sometimes a closed-loop system might fall into unstable state by adjusted control parameters. With all these factors, it is considered that a model-based controller is particularly advantageous controller focusing on a stability, on the opposite side, a data-oriented controller is advantageous when it is required to improve the tracking property and costs.

By the way, there are few cases that a mathematical model of a controlled object is completely unknown in process systems such as heat processes. Moreover, in most cases, ranges of values of the constant time, the system gain, and time-lag of the system can be taken by some prior information. In such a situation, designing 2 degree-of-freedom controller (2DOF) [8] is an effective measure: a closed-loop system is composed by a robust controller which is designed by prior information of a system and the tracking property is compensated by a feedforward compensator. In addition, if a feedforward compensator becomes unstable then the compensator can be cut off from the loop, and the stability of the closed-loop can be guaranteed. Therefore an aggressive design can do, and it is considered that a data-oriented design scheme is a effective method for designing a feedforward compensator for this reason.

In this paper, a data-oriented hybrid 2DOF nonlinear controller design scheme is proposed. According to the proposed method, a closed-loop system is first composed based on a robust stability by using prior information of a system, and a feedforward compensator is tuned by using closed-loop data obtained by the closed-loop system so that the 2DOF control system can achieve a desired tracking property. More specifically, in a nonlinear process system, it has an assumption that some prior information (the constant time, the system gain and the time-lag) is given, a robust PID controller based on generalized minimum variance control (GMVC) is first designed. Next, a set of experimental data is obtained by using the closed-loop system, and a nonlinear feedforward PD compensator composed by cerebellar model articulation controller (CMAC) is learned by using the data in an offline manner. The CMAC-FRIT method [9] is employed in this learning. This method can easily apply to real systems, because it tries to improve tracking property in addition to

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guarantee a robustness of the closed-loop system. Moreover, the proposed method is effective for nonlinear systems because CMAC-PD compensator absorb system's nonlinearity. In this paper, the design method of the proposed control system is first presented and the effectiveness of the proposed controller is evaluated by a simulation.

II. Robust feedback controller design

A. Design of GMV-PID controller

It is assumed that a nonlinear process system can locally be described as the following linear system at each equilibrium point:

$$A(z^{-1})y(t) = z^{-(k+1)}B(z^{-1})u(t) + \frac{\xi(t)}{\Delta}, \tag{1}$$

$$\left.\begin{array}{l} A(z^{-1}) = 1 + a_1 z^{-1} + a_2 z^{-2} \\ B(z^{-1}) = b_0 + b_1 z^{-1} \end{array}\right\}. \tag{2}$$

In (1), $u(t)$ and $y(t)$ represent the control input and the system output, respectively; k is the time-lag ; and $\xi(t)$ is the white Gaussian noise with zero mean and variance σ^2. Here, z^{-1} denotes the backward operator: $z^{-1}y(t) = y(t-1)$; Δ is the differencing operator: $\Delta := 1 - z^{-1}$. The model described in (1) is the so-called CARIMA (controlled auto-regressive and integrated moving average) model that has been frequently utilized in the process industries.

The GMVC law for (1) is derived to minimize the following criterion:

$$J_1 = E[\phi^2(t+k+1)], \tag{3}$$

where $\phi(t+k+1)$ is the generalized output given by following equation:

$$\phi(t+k+1) := y(t+k+1) + \lambda\Delta u(t) - r(t). \tag{4}$$

In (4), $r(t)$ denotes the step reference signal and λ is the weight coefficient for the differential control input $\Delta u(t)$. λ is set considering a robustness of a closed-loop system. Next, the following Diophantine equation is introduced:

$$1 = \Delta E(z^{-1})A(z^{-1}) + z^{-(k+1)}F(z^{-1}), \tag{5}$$

$$\left.\begin{array}{l} E(z^{-1}) = 1 + e_1 z^{-1} \cdots + e_k z^{-k} \\ F(z^{-1}) = f_0 + f_1 z^{-1} + f_2 z^{-2} \end{array}\right\}, \tag{6}$$

where the orders of $E(z^{-1})$ and $F(z^{-1})$ are determined to calculate these coefficients uniquely from $\Delta A(z^{-1})$.

From (3), (4), and (5), the GMVC law to minimize the criterion J_1 can be derived by $\hat{\phi}(t+k+1|t) = 0$. The control law is described by the following equation:

$$\Delta u(t) = \frac{1}{G(z^{-1}) + \lambda} r(t) - \frac{F(z^{-1})}{G(z^{-1}) + \lambda} y(t). \tag{7}$$

where,

$$G(z^{-1}) := E(z^{-1})B(z^{-1}). \tag{8}$$

As a more detail derivation of equation (7), see the article [10].

B. Conversion into PID control law

Next, the control parameters computed using the GMVC are converted into PID gains. The velocity type of the PID control law is given by the following equation:

$$\Delta u(t) = K_I e(t) - K_P \Delta y(t) - K_D \Delta^2 y(t), \tag{9}$$

where $e(t)$ expresses the following control error:

$$e(t) := r(t) - y(t). \tag{10}$$

K_P, K_I, and K_D denote the proportional gain, integral gain, and derivative gain. By replacing the polynomial $G(z^{-1})$ in (7) by the steady-state term $G(1)$, the following equation can be obtained:

$$\Delta u(t) = \frac{1}{G(1) + \lambda} r(t) - \frac{F(z^{-1})}{G(1) + \lambda} y(t). \tag{11}$$

By comparing the coefficients of (9) and (11), the following relationship between the control parameters and PID gains can be obtained:

$$K_P = -\frac{f_1 + 2f_2}{G(1) + \lambda}, \tag{12}$$

$$K_I = \frac{f_0 + f_1 + f_2}{G(1) + \lambda}, \tag{13}$$

$$K_D = \frac{f_2}{G(1) + \lambda}. \tag{14}$$

Using this permutation, the GMV controller is approximately replaced by the PID controller.

C. Procedure for determining λ based on robust stability

1) Robust stability condition: It is supposed that a nominal frequency transfer function for a controlled object is $P(j\omega)$ and a frequency transfer function of a real process is $\tilde{P}(j\omega)$. Then $\tilde{P}(j\omega)$ can be described as follows:

$$\tilde{P}(j\omega) = \{1 + h(j\omega)\}P(j\omega), \tag{15}$$

where $h(j\omega)$ indicates a multiplicative uncertainty. Moreover, if $h_m(\omega)$ which is satisfied the following relationship exists:

$$|h(j\omega)| \leq h_m(\omega), \tag{16}$$

and it is supposed that a closed-loop frequency transfer function including a controller is $W(j\omega)$, it is well-known that the following condition is a necessary and sufficient condition for a robust stability of the control system.

$$|W(j\omega)|h_m(\omega) < 1. \tag{17}$$

2) λ design: A nominal plant of a controlled object is designed as follows:

$$\begin{aligned} G(s) &= \frac{K}{1+\tau s} e^{-Ls} \\ &\simeq \frac{K}{(1+\tau s)(1+Ls)}, \end{aligned} \tag{18}$$

note that the second equation is a model whose time-lag is approximated by a 1st-order system. Next, the following perturbation model for (18) is considered:

$$\tilde{G}(s) = \frac{\tilde{K}}{1+\tilde{\tau}s}e^{-\tilde{L}s} \simeq \frac{\tilde{K}}{(1+\tilde{\tau}s)(1+\tilde{L}s)}, \quad (19)$$

where, $\tilde{\tau}, \tilde{K}$, and $\tilde{L}$ are defined as follows:

$$\left.\begin{array}{r}\tau(1-\delta) \leq \tilde{\tau} \leq \tau(1+\delta) \\ K(1-\delta) \leq \tilde{K} \leq K(1+\delta) \\ L(1-\delta) \leq \tilde{L} \leq L(1+\delta)\end{array}\right\}. \quad (20)$$

In (20), δ expresses a perturbation rate, and it is set between $0 < \delta < 1$ considering the uncertainty of the model. In this research, λ is determined from the view point of robust stability by using following discrete-time models corresponding to (18) and (19):

$$\alpha(z^{-1})y(t) = z^{-1}\beta(z^{-1})u(t), \quad (21)$$

$$\tilde{\alpha}(z^{-1})y(t) = z^{-1}\tilde{\beta}(z^{-1})u(t), \quad (22)$$

where,

$$\left.\begin{array}{l}\alpha(z^{-1}) = 1+\alpha_1 z^{-1}+\alpha_2 z^{-2} \\ \beta(z^{-1}) = \beta_0+\beta_1 z^{-1}\end{array}\right\}, \quad (23)$$

$$\left.\begin{array}{l}\tilde{\alpha}(z^{-1}) = 1+\tilde{\alpha}_1 z^{-1}+\tilde{\alpha}_2 z^{-2} \\ \tilde{\beta}(z^{-1}) = \tilde{\beta}_0+\tilde{\beta}_1 z^{-1}\end{array}\right\}. \quad (24)$$

In addition, $P(z^{-1})$ and $\tilde{P}(z^{-1})$ corresponding to (15) is defined as follows:

$$\left.\begin{array}{l}P(z^{-1}) := z^{-1}\beta(z^{-1})/\alpha(z^{-1}) \\ \tilde{P}(z^{-1}) := z^{-1}\tilde{\beta}(z^{-1})/\tilde{\alpha}(z^{-1})\end{array}\right\}. \quad (25)$$

Applying (25) to (15), the following equation about a multiplicative uncertainty can be obtained:

$$h(z^{-1}) = \frac{\tilde{P}(z^{-1})-P(z^{-1})}{P(z^{-1})} \quad (26)$$

$$= \frac{\alpha(z^{-1})\tilde{\beta}(z^{-1})-\tilde{\alpha}(z^{-1})\beta(z^{-1})}{\alpha(z^{-1})\beta(z^{-1})}. \quad (27)$$

Moreover, a transfer function $W(z^{-1})$ can be described as follows:

$$W(z^{-1}) = \frac{z^{-1}K_I\beta(z^{-1})}{\Delta\alpha(z^{-1})+z^{-1}\beta(z^{-1})C(z^{-1})}, \quad (28)$$

where,

$$C(z^{-1}) = c_0+c_1 z^{-1}+c_2 z^{-2}, \quad (29)$$

$$\left.\begin{array}{l}c_0 = -(K_P+K_I+K_D) \\ c_1 = K_P+2K_D \\ c_2 = -K_D\end{array}\right\}. \quad (30)$$

$h(j\omega)$ in (15) and $W(j\omega)$ in (17) are obtained from (27) and (28) using the relationship $z = e^{j\omega T_s}$, respectively. In GMV-PID control system, the value of λ affects only the proportional gain. Therefore a robust PID control system can be composed by designing λ in order to satisfy (17).

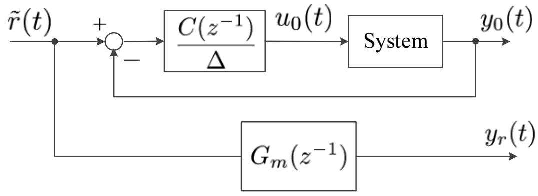

Fig. 2. Block diagram of fictitious reference iterative tuning (FRIT).

III. Feedforward CMAC-PD compensator design

This section presents a design method of data-oriented feedforward compensator by using CMAC.

A. CMAC

CMAC is a mathematical model of an information-processing mechanism of the cerebellar cortex in humans. The schematic diagram of a CMAC is shown in Figure 1, and a sequence of actions of the CMAC is explained. First, an input vector of $(3, 6)$ is given to the input space, which is then converted into the labeled set $\{B, c\}, \{F, g\}$, and $\{J, k\}$. Based on these labels, a weight table of $8, 9$, and 3 is referenced that outputs 20 as the total. For example, if 14 is the desired output, then the difference between the output and the teaching signal is divided by the number of weight tables, and the value is fed back into the weight tables. That is, learning is performed when $(14-20)/3$ is inserted back into the weight tables as a corrective term. Therefore, when compared, it is shown that CMAC is capable of learning faster than a hierarchical NN. The example described above deals with an input space of two dimensions for a simplified illustration; however, in the CMAC-PID controller, a CMAC with three dimensions is used, which is defined as $r(t)$, $e(t)$, and $\Delta e(t)$. This time, the total number of each label, n_1, n_2, and n_3 becomes $n_1 \times n_2 \times n_3$, and the weight table is discretized into N pieces.

B. FRIT

FRIT is a method to compute control parameters directly using a fictitious reference signal generated by the closed-loop data. The block diagram of the FRIT method is shown in Figure 2. Where, $u_0(t)$ and $y_0(t)$ express the control input and the control output in the closed-loop data, respectively. $C(z^{-1})/\Delta$ is a controller and $C(z^{-1})$ expresses a PID controller. The fictitious reference signal $\tilde{r}(t)$ is derived as follows:

$$\tilde{r}(j) = C^{-1}(z^{-1})u_0(t) + y_0(t). \quad (31)$$

In the FRIT method, the following criterion is first defined, and the control parameters are determined to minimize the criterion:

$$J_2(t) = \frac{1}{2}\left\{y_0(t) - y_r(t)\right\}^2. \quad (32)$$

In (32), $y_r(t)$ indicates the output from a reference model $G_m(z^{-1})$. The reference model $G(z^{-1})$ is designed as follows:

$$G_m(z^{-1}) := \frac{z^{-1}T(1)}{T(z^{-1})}, \quad (33)$$

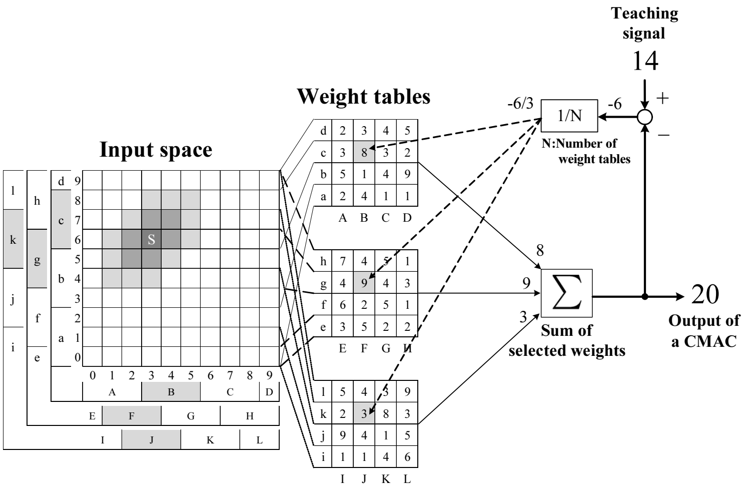

Fig. 1. Structure of cerebellar model articulation controller (CMAC).

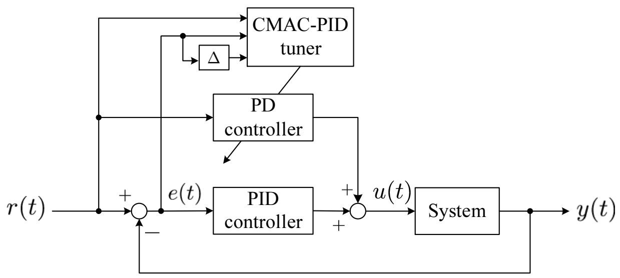

Fig. 3. Block diagram of 2-degree-of-freedom (2DOF) nonlinear control system.

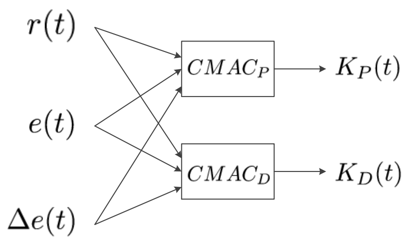

Fig. 4. Block diagram of CMAC-PD tuner.

where, $T(z^{-1})$ is a design polynomial defined as follows:

$$T(z^{-1}) = 1 + t_1 z^{-1} + t_2 z^{-2}, \tag{34}$$

$$\left.\begin{array}{l} t_1 = -2e^{-2\rho} \\ t_2 = e^{-4\rho} \\ \rho = T_s/\sigma \end{array}\right\}. \tag{35}$$

In (35), T_s is the sampling time. The rise time σ is a parameter related to the rise time of a control system, and it is arbitrarily set by an operator.

C. Offline learning of Feedforward CMAC-PD compensator

A 2DOF control system using a PD compensator with CMAC-PD tuner (CMAC-PD compensator) is composed as shown in Fig. 3. The CMAC-PD tuner is composed as shown in Fig. 4. Weight tables of the CMAC-PD tuner is learned by using obtained experimental data in an offline manner. First, the CMAC-PD tuner outputs PD gains at t step depending on $r_0(t), e_0(t)$ and $\Delta e_0(t)$. Where, $r_0(t)$ and $e_0(t)$ expresses the reference signal and the controlled error at t[step] in the closed-loop data as the follows:

$$\left.\begin{array}{l} K_{Pf}(t) = \sum_{h=1}^{N} W_{P,h}^{old} \\ K_{Df}(t) = \sum_{h=1}^{N} W_{D,h}^{old} \end{array}\right\}, \tag{36}$$

where, $W_{\{P,D\},h}^{old}$ is a weight referenced from the h-th table of $CMAC_{\{P,D\}}$ in Fig. 4. Next, the CMAC-PD tuner learning is performed based on the minimization of (32). Each tuner's learning method is given as follows:

$$\left.\begin{array}{l} W_{P,h}^{new} = W_{P,h}^{old} - \eta_P \dfrac{\partial J(t+1)}{\partial K_P(t)} \dfrac{1}{N} \\ W_{D,h}^{new} = W_{D,h}^{old} - \eta_D \dfrac{\partial J(t+1)}{\partial K_D(t)} \dfrac{1}{N} \\ \qquad (h = 1, \ldots, N) \end{array}\right\}, \tag{37}$$

where,

$$\left.\begin{array}{l} \dfrac{\partial J(t+1)}{\partial K_P(t)} = \dfrac{\partial J(t+1)}{\partial y_r(t+1)} \dfrac{\partial y_r(t+1)}{\partial \tilde{r}(t)} \dfrac{\partial \tilde{r}(t)}{\partial K_P(t)} \\ \dfrac{\partial J(t+1)}{\partial K_D(t)} = \dfrac{\partial J(t+1)}{\partial y_r(t+1)} \dfrac{\partial y_r(t+1)}{\partial \tilde{r}(t)} \dfrac{\partial \tilde{r}(t)}{\partial K_D(t)} \end{array}\right\}. \tag{38}$$

η_P and η_D indicate learning coefficients. A learned CMAC-PD tuner can be obtained by performing these learning processes until minimizing the value of (32). The design procedure of the proposed 2DOF nonlinear controller is summarized as follows:

[2DOF nonlinear controller design algorithm]

Step 1: A robust GMV-PID controller is designed based on prior information of a controlled object.

Step 2: A control system shown in Fig.3 is first composed and performs control in order to get initial experimental data.

Step 3: A CMAC-PD tuner is learned based on (37) by using experimental data.

Step 4: Repeat Step 3 until J_2 becomes enough small.

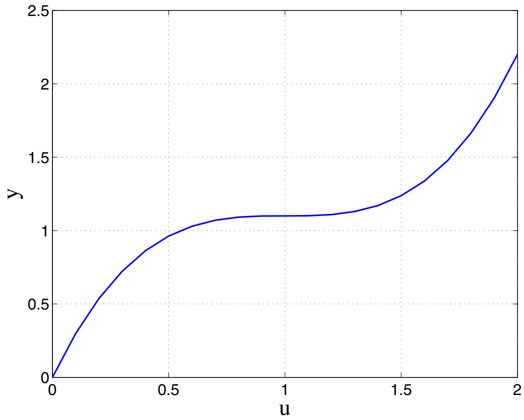

Fig. 5. Static property of Hammerstein model.

IV. Numerical Example

In order to verify the effectiveness of the proposed method, the method is applied to the following Hammerstein model:

$$\left.\begin{array}{l} y(t) = 0.6y(t-1) - 0.1y(t-2) \\ \qquad +1.2x(t-1) - 0.1x(t-2) + \xi(t) \\ x(t) = 1.5u(t) - 1.5u^2(t) + 0.5u^3(t) \end{array}\right\}, \tag{39}$$

where $\xi(t)$ is white Gaussian noise with zero mean and variance 1.0×10^{-3}. In addition, the sampling time T_s is set as 1.0[s] in the simulation. Fig. 5 shows the static property of the system. At each step the reference signal is set by the following equation:

$$r(t) = \begin{cases} 1.0 (0 \le t < 50) \\ 2.5 (50 \le t < 100) \\ 0.5 (100 \le t < 150). \end{cases} \tag{40}$$

First, a nominal plant of the system is given as the following equation:

$$G(s) = \frac{K}{(1+\tau s)(1+Ls)}, \tag{41}$$

where, each parameters are set as follows:

$$\tau = 1.18, \ K = 2.37, \ L = 2.48. \tag{42}$$

PID parameters based on GMVC are designed as follows considering an uncertainty of the model (41):

$$K_P = 0.19, \ K_I = 0.184, \ K_D = 0.0524. \tag{43}$$

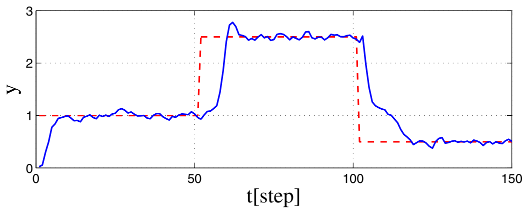

Fig. 6. Closed-loop data using robust GMV-PID controller

TABLE I
Design parameters for cerebellar model articulation controller (CMAC).

Number of labels	$n1 = n2 = n3 = 9$
Number of weight tables	$N = 6$
Learning coefficients	$\eta_P = 1.0 \times 10^{-2}$
	$\eta_D = 1.0 \times 10^{-2}$

The control results obtained using the robust GMV-PID controller is shown in Fig. 6. The result shows that the robustness of the controller is guaranteed, and the system output follows each reference value. However, when the reference value is changed from $r(t) = 2.5$ to $r(t) = 0.5$, the result shows its tracking property degrades when the output passes through around $y(t) = 1.0$ where the system gain is smaller.

Next, the proposed CMAC-PD compensator is applied to the closed-loop system whose PID gains are fixed previous values. The specific design parameters to compose the CMAC-PD compensator are shown in TABLE I. A reference model is designed as follows:

$$G(z^{-1}) = \frac{0.5423z^{-1}}{1 - 0.527z^{-1} + 0.0695z^{-2}}. \tag{44}$$

After these settings, offline learning of the CMAC-PD tuner is performed by using the closed-loop data. Where, the result of Fig. 6 is employed as the closed-loop data. Moreover, it is necessary to stop learning when the CMAC-PD tuner has learned enough. Thus, in this simulation, the following integrated squared error (ISE) index is defined:

$$I = \frac{1}{M} \sum_{t=1}^{N} \{y_0(t) - y_r(t)\}^2, \tag{45}$$

where, M is the number of data in the closed-loop data. It is considered that the learning process has completed sufficiently when the index is converged on a minimum value. A transition of the ISE index of this simulation is shown in Fig. 7. From Fig. 7, the index is converged around 200 iterations, thus a CMAC-PD tuner learned 200 iterations is employed in this simulation.

The control result obtained using the proposed 2DOF nonlinear controller is shown in Fig. 8. In this figure, $y_d(t)$ is the output from the reference model $G_m(z^{-1})$ corresponding to the reference signal $r(t)$. Trajectories of the system input $u(t)$, the output from the CMAC-PD compensator $u_f(t)$,

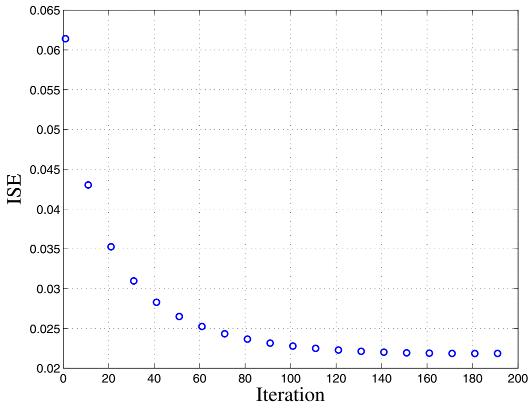

Fig. 7. Trajectory of integrated squared error (ISE) index.

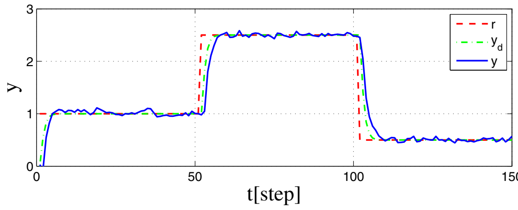

Fig. 8. Control result obtained using proposed 2DOF nonlinear controller.

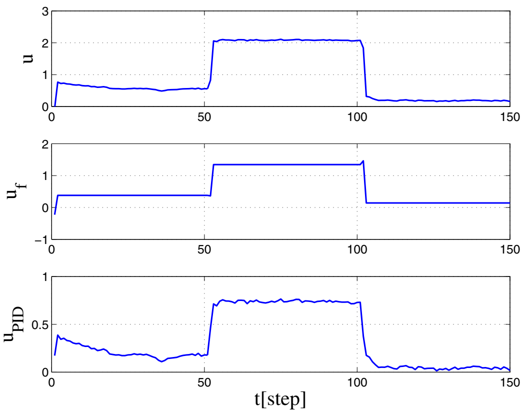

Fig. 9. Trajectories of each controller output.

and the output of the robust GMV-PID controller $u_{PID}(t)$ corresponding to Fig. 8 are shown in Fig. 9. In addition, the trajectories of the PD gains are shown in Fig. 10. From these results, the feedforward compensator changes its gains in order to obtain the desired tracking property at each equilibrium point, and a good control result can be obtained.

V. Conclusions

In this paper, the design scheme of data-oriented 2DOF nonlinear controller is presented. According to the method, a robust PID control system based on GMVC is first designed, and a data-oriented PD compensator is also applied in order to improve the tracking property of the control system. In a previous data-oriented controller design scheme, it is

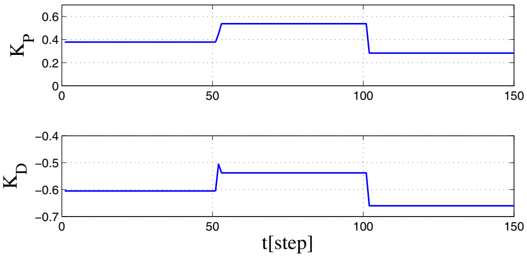

Fig. 10. Trajectories of PD gains.

difficult to guarantee a stability of a closed-loop system because it uses only a closed-loop data without using prior information of a system. In this method, a stability of a closed-loop system is first guaranteed based on the robust stability theory. If reliability of the obtained model from the information is low then it guarantees the stability by liberally estimating its uncertainty. After that, the CMAC-PD compensator learns its weight tables by using a set of closed-loop data obtained by the closed-loop system is added to the system. The effectiveness of the proposed method is evaluated by a simulation.

In a future work, a design method of a performance-driven controller will be considered; it evaluates a control performance of the CMAC-PD compensator and determines whether or not to break away from the control system.

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