Design of a Data-Driven Control System for a Hydraulic Excavator

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Abstract

PID control schemes have been widely used in most industrial systems. However, it is difficult to achieve the desired control performance for nonlinear systems such as hydraulic excavators by using fixed PID parameters. In order to overcome such a problem, data-driven PID control scheme based on database has been proposed. Moreover, data-driven scheme has a learning method in off-line by using closed-loop data. In this paper, data-driven control scheme is applied to a hydraulic excavator to get desired control performance.

Keywords: PID controller, Data-driven controller, Hydraulic excavators, off-line learning.

1. Introduction

In most industries, it is very important to get desired control performance by using some control schemes. PID control schemes[1, 2] have been widely used because control parameters have a clear physical meaning and control structure is simple. However, it is very difficult to get desired control performance for nonlinear systems such as hydraulic excavators by using fixed PID parameters.

In order to overcome such problem, data-driven PID control scheme[3] based on database has been proposed. It is a controller for nonlinear system and it has an off-line learning method by using closed-loop data.

In this paper, data-driven control scheme is applied to a hydraulic excavator to improve control performance. The effectiveness of the proposed scheme is numerically verified by using a simulation example.

2. Schematic Figure of a Hydraulic System

Fig.1 shows schematic of a hydraulic system[4]. As the system, the motion of system is swing operation. The input should be the direction of flow rate for a hydraulic pump, and the output should be this torque. In the system, the relief valve works in order to prevent increasing hydraulic pressure. Therefore, the hydraulic system is a kind of time-variant system include a derivative element after the relief valve work. That why, it is difficult to get desired control performance by using fixed controller.

3. Schematic of Data-Driven Control System

Schematic of data-driven control system is shown in fig.2. The current information of controlled object is stored in a database and suitable control parameters are calculated by historical data in the database. Moreover, off-line learning method is utilized to avoid on-line learning time cost. The specific design procedure of data-driven scheme is described in section **7**.

4. Controlled Object

A controlled object can be described by following nonlinear system:

$$y(t) = f\big(\phi(t-1)\big), \tag{1}$$

where $y(t)$ is system output, $f(\cdot)$ is function of nonlinear and $\phi(t-1)$ is information vector. $\phi(t-1)$ is defined as follows:

$$\boldsymbol{\phi}(t-1) := [y(t-1), \cdots, y(t-n_y), u(t-1), \cdots, u(t-n_u)], \tag{2}$$

where $u(t)$ is system input, and n_y, n_u are the order of system output and input respectively. In data-driven control scheme, I/O data (equation (2)) are stored in the database.

5. Control law

Hydraulic system in Fig. 1 has derivative element. Therefore, controller with double integral element is needed and PII^{2}D controller is defined as follows:

$$\Delta^2 u(t) = K_{II} e(t) + K_I \Delta e(t) - K_P \Delta^2 y(t) - K_D \Delta^3 y(t) \tag{3}$$

$$e(t) := r(t) - y(t), \tag{4}$$

where $e(t)$ denotes control error, and K_P, K_I, K_D and K_{II} respectively are proportional gain, integral gain, derivative gain and double integral gain. Furthermore, Δ denotes a difference operator.

6. Fictitious Reference Iterative Tuning: FRIT

FRIT[5] is a scheme to calculate control parameters directly from closed-loop data which are input $u_0(t)$, output $y_0(t)$ and $e_0(t) = \tilde{r}(t) - y_0(t)$.

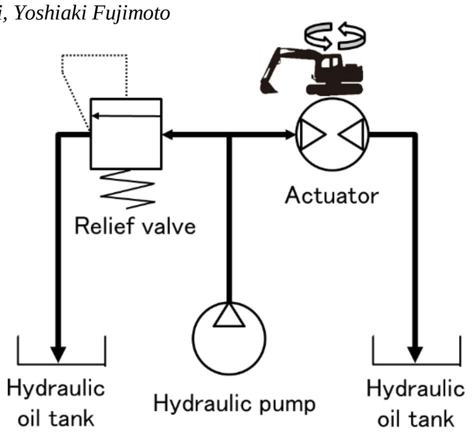

Fig. 1. Schematic of a hydraulic system.

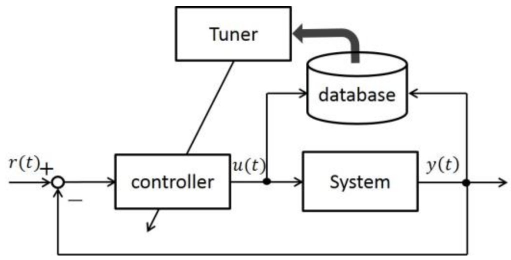

Fig. 2. Schematic of the data-driven control system.

$$\Delta^2 u_0(t) = K_{II} e_0(t) + K_I \Delta e_0(t) - K_P \Delta^2 y_0(t) - K_D \Delta^3 y_0(t) \tag{5}$$

Therefore, $\tilde{r}(t)$ is derived as follows:

$$\tilde{r}(t) = [\Delta^2 u_0(t) + K_I \tilde{r}(t-1) + \Delta^2 K_P y_0(t) + \Delta K_I y_0(t) + \Delta^3 y_0(t) + K_{II} y_0(t)]/(K_{II} + K_I). \tag{6}$$

In addition, user set a desired reference model expressed by following equation:

$$\tilde{y}_m(t) = \frac{z^{-1}P(1)}{P(z^{-1})}\tilde{r}(t), \tag{7}$$

where $\tilde{y}_m(t)$ is reference model output and $P(z^{-1})$ is user-specified polynomial. In FRIT, Control parameters are calculated to minimize difference between $\tilde{y}_m(t)$ and $y(t)$.

Here, $P(z^{-1})$ is designed based on the reference design as follows:

$$P(z^{-1}) := 1 + p_1 z^{-1} + p_2 z^{-1} \tag{8}$$

$$\left.\begin{aligned} p_1 &= -2\exp\left(-\frac{\rho}{2\mu}\right)\cos\left(\frac{\sqrt{4\mu-1}}{2\mu}\rho\right) \\ p_2 &= \exp\left(-\frac{\rho}{\mu}\right) \\ \rho &:= \frac{T_s}{\sigma} \\ \mu &:= 0.25(1-\delta) + 0.51\delta \end{aligned}\right\}, \tag{9}$$

where σ is a parameter related to the rise-time and δ is a parameter related to the damping oscillation. User set them arbitrarily. σ denotes the time when output reaches about 60% of the step reference value. Moreover, δ is set between $0 \leq \delta \leq 2.0$ desirably. In particular, $\delta = 0$ indicates the response of Butterworth model and $\delta = 1.0$ indicates the response of Binominal model.

7. Design of a Data-Driven Controller

7.1. *Design procedure*

[STEP 1] Create an initial database.
The historical data is needed to use data-driven control scheme. Therefore, initial database is created by using Zieglar & Nichols: ZN method[1] and Chien, Hrones & Reswick: CHR method[2]. The database are constructed by following information vector:

$$\boldsymbol{\phi}(j) := [\bar{\boldsymbol{\phi}}(j), \boldsymbol{K}(j)] \qquad (j = 1,2,,\cdots,N) \tag{10}$$

$$\bar{\boldsymbol{\phi}}(j) := [r(t+1), r(t), y(t), \cdots, y(t-n_y+1), u(t-1), \cdots, u(t-n_u)] \tag{11}$$

$$\boldsymbol{K}(j) := [K_P(t), K_I(t), K_D(t), K_{II}(t)], \tag{12}$$

where N denotes the number of data. Since initial control parameters are fixed, which indicates $\boldsymbol{K}(1) = \boldsymbol{K}(2) = \cdots = \boldsymbol{K}(N)$.

[STEP 2] Calculate distance and select neighbors' data.
Distance between Query $\bar{\boldsymbol{\phi}}(t)$ and $\bar{\boldsymbol{\phi}}(j)$ is calculated by using the following L1–norm with some weights:

$$d\left(\bar{\boldsymbol{\phi}}(t), \bar{\boldsymbol{\phi}}(j)\right) = \sum_{l=1}^{m_y+n_u+1} \left| \frac{\bar{\boldsymbol{\phi}}_l(t) - \bar{\boldsymbol{\phi}}_l(j)}{\max\bar{\boldsymbol{\phi}}_l(m) - \min\bar{\boldsymbol{\phi}}_l(m)} \right|. \tag{13}$$

$$(j = 1,2,,\cdots,N)$$

$\bar{\boldsymbol{\phi}}_l(j)$ denotes the lth element of query $\bar{\boldsymbol{\phi}}(j)$. $\max\bar{\boldsymbol{\phi}}_l(m)$ is a maximum lth element in database. In contrast, $\min\bar{\boldsymbol{\phi}}_l(m)$ is a minimum lth element. In addition, the number of neighbors' data k are selected, which data are based on smallest distance d.

[STEP 3] Calculate control parameters.
Control parameters are calculated by using the following linearly weighted average (LWA):

$$\boldsymbol{K}(\mathrm{t}) = \sum_{i=1}^{k} w_i \boldsymbol{K}(i), \quad \sum_{i=1}^{k} w_i = 1, \tag{14}$$

where w_i is the weight corresponding to the i th information vector $\bar{\boldsymbol{\phi}}(i)$ in the selected neighbors. It is calculated by following equation:

$$w_i = \frac{1/d_i}{\sum_{i=1}^{k} 1/d_i}. \tag{15}$$

In order to calculate effective control parameters, a learning method is needed. Therefore, an off-line learning method is described in next section.

7.2. *Off-line learning method in Data-Driven Control scheme by using FRIT*

In this section, an off-line learning method is described by using FRIT. At first, the number of neighbors' data k is selected and $\boldsymbol{K}^{old}(t)$ is calculated by equation (14) using closed-loop data $u_0(t)$ and $y_0(t)$. Next, the following steepest descent method is utilized to modify the control parameters:

$$\boldsymbol{K}^{new}(t) = \boldsymbol{K}^{old}(t) - \boldsymbol{\eta}\frac{\partial J(t+1)}{\partial \boldsymbol{K}(t)} \tag{16}$$

$$\boldsymbol{\eta} = [\eta_P, \eta_I, \eta_D, \eta_{II}],$$

where $\boldsymbol{\eta}$ denotes the learning rate and $J(t+1)$ is defined as following error criterion:

$$J(t) := \frac{1}{2}\epsilon(t)^2 \tag{17}$$

$$\epsilon(t) := y_0(t) - \tilde{y}_m(t), \tag{18}$$

The each partial differential of equation (16) are developed as follows:

$$\left.\begin{aligned}
\frac{\partial J(t+1)}{\partial K_P(t)} &= \frac{\partial J(t+1)}{\partial \tilde{y}_m(t+1)}\frac{\partial \tilde{y}_m(t+1)}{\partial \tilde{r}(t)}\frac{\partial \tilde{r}(t)}{\partial K_P(t)} \\
&= \frac{\epsilon(t+1)P(1)\Delta^2 y_0(t)}{K_I + K_{II}} \\
\frac{\partial J(t+1)}{\partial K_I(t)} &= \frac{\partial J(t+1)}{\partial \tilde{y}_m(t+1)}\frac{\partial \tilde{y}_m(t+1)}{\partial \tilde{r}(t)}\frac{\partial \tilde{r}(t)}{\partial K_I(t)} \\
&= \frac{\epsilon(t+1)P(1)\Delta y_0(t)}{K_I + K_{II}} \\
\frac{\partial J(t+1)}{\partial K_D(t)} &= \frac{\partial J(t+1)}{\partial \tilde{y}_m(t+1)}\frac{\partial \tilde{y}_m(t+1)}{\partial \tilde{r}(t)}\frac{\partial \tilde{r}(t)}{\partial K_D(t)} \\
&= \frac{\epsilon(t+1)P(1)\Delta^3 y_0(t)}{K_I + K_{II}} \\
\frac{\partial J(t+1)}{\partial K_{II}(t)} &= \frac{\partial J(t+1)}{\partial \tilde{y}_m(t+1)}\frac{\partial \tilde{y}_m(t+1)}{\partial \tilde{r}(t)}\frac{\partial \tilde{r}(t)}{\partial K_{II}(t)} \\
&= \frac{\epsilon(t+1)P(1)\{y_0(t) - \tilde{r}(t-1)\}}{K_I + K_{II}}
\end{aligned}\right\}. \tag{19}$$

Therefore, control parameters can be learned off-line by using closed-loop data in equation (16) and (19).

8. Numerical Example

In this section, the effectiveness of the proposed scheme is verified. Table 1 shows the user-specified parameters included in proposed scheme.
Fig. 3 shows control results by using fixed PII^{2}D control and proposed scheme. Initial control parameters in fixed PII^{2}D controller are set as follows:

Table 1. User-specified parameters included in proposed scheme.

Rise-time	$\sigma = 0.2$
Damping property	$\delta = 0$
Order of information vector	$n_u = 4, n_y = 3$
Learning rate : $t \leq 4.0$[s]	$\boldsymbol{\eta} = [2 \times 10^{-13}, 10^{-15}, 10^{-13}, 0]$
: $t > 4.0$[s]	$\boldsymbol{\eta} = 3 \times [10^{-24}, 10^{-24}, 10^{-24}, 10^{-24}]$
Number of neighbors' data	$k = 3$
Reference signal	$r = 100$

$$K_P = 1.8 \times 10^{-6}, K_I = 9.0 \times 10^{-8}, K_D = 1.8 \times 10^{-5}, K_{II} = 0. \quad (20)$$

In equation (20), K_{II} equals to zero because this parameter is for a system without derivative element between $t = 2$[s] - 4.0 [s]

In this case, system output can be reached to reference signal between $t = 2$[s] - 4.0 [s]. However, after 4.0[s], it cannot be reached to reference signal because the system includes derivative element.

In proposed scheme, control performance is better than above control result since control parameters are adjusted. Trajectories of control parameters are show in Fig. 4. K_{II} is adjusted largely after $t = 4$[s] because system has derivative elements.

9. Conclusion

This paper has proposed a data-driven control system for a hydraulic excavator. Control parameters should be adjusted because a hydraulic excavator is nonlinear system. In this paper, controller has been designed as PII^{2}D controller for derivative system. The effectiveness of proposed scheme has been numerically verified by using simulation example.

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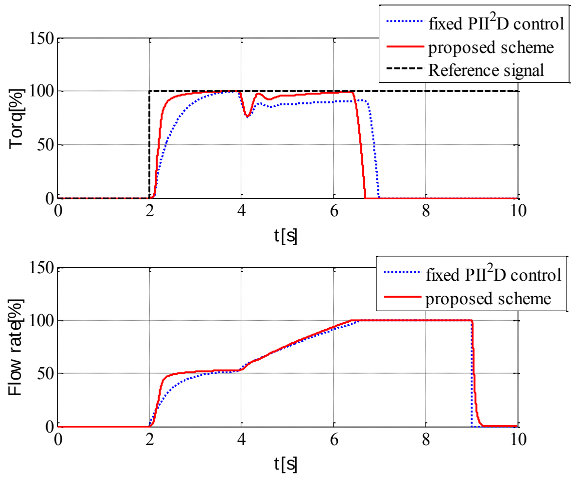

Fig. 3. Control results by fixed PII^{2}D control and proposed scheme.

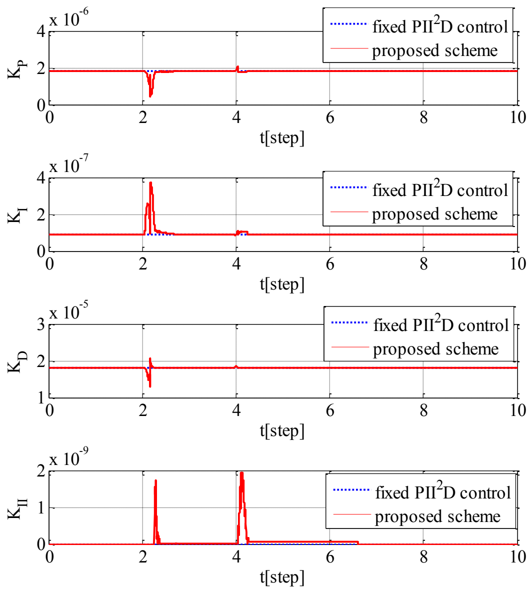

Fig. 4. Trajectories of control parameters corresponding to Fig. 3.