Design of Data-driven Multi-agent Systems

Kenta Nagao, Natsuki Kawaguchi, Takao Sato
Graduate School of Engineering, University of Hyogo
2167, Shosha, Himeji, Hyogo 671-2280, Japan
E-mail: {Kawaguchi, tsato}[AT]eng.u-hyogo.ac.jp

Abstract

This study discusses the consensus control of multi-agent systems. The consensus can be achieved when the closed-loop system of multi-agent systems is stable. In conventional model-based methods, since the controller is designed based on the dynamic characteristics of the agents, models of the agents must be used. On the other hand, this study examines data-driven design of multi-agent systems. In the proposed method, the controller of a multi-agent system is designed directly from the control data, where the controller structure is fixed. The usefulness of the proposed method is shown through numerical examples.

Keywords: Multi-agent Systems, Data-driven Control

1. Introduction

In multi-agent systems [1], multiple agents interact with each other and act autonomously to achieve global objectives. Many design methods have been proposed for multi-agent systems, but most of them are model-based design, which requires process models. Therefore, model-free adaptive control has been proposed for designing multi-agent systems with unknown dynamics [2]. In this method, the control system is designed by identifying an unknown model. On the other hand, a data-driven design method for designing a controller directly from data has also been proposed [3]. The data-driven design approach eliminates the need for process models that are required in the model-based approach. Therefore, this study examines a data-driven design method for multi-agent systems that does not require models of agents.

2. Data-driven Design

Consider the model reference problem for agent i shown in Fig. 1, where $P_i(z^{-1})$, $C_i(z^{-1}, \theta_i)$, and $M_i(z^{-1})$ are the process model, controller, and reference model, respectively, $u_i(k)$ and $y_i(k)$ are the process input and process output, respectively, and $r_i(k)$ and $y_{Mi}(k)$ are the reference input and reference model output, respectively. The reference input consists of $r_{ij}(k)$ $(j = 1, \cdots, d_i)$ given by adjacent agents, where d_i denotes the number of adjacent agents of agent i.

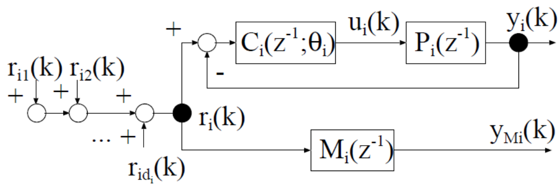


Fig. 1 Block diagram of the model reference problem of a multi-agent system

Assumption

The process model $P_i(z^{-1})$ is unknown.

The controller parameters θ_i is optimized by minimizing the following objective function:

$J_{iMR}(\theta_i) =$

$$\left\|\left(\frac{P_i(z^{-1})C_i(z^{-1},\theta_i)}{1+d_iP_i(z^{-1})C_i(z^{-1},\theta_i)}-M_i(z^{-1})\right)W_i(z^{-1})\right\|_2^2, (1)$$

where $W_i(z^{-1})$ denote a design parameter. Since the objective function involves an unknown process model, it cannot be minimized as is. Instead of the objective function, the controller parameters are determined based on the following function:

$$J_{iVR}(\theta_i) = \frac{1}{N}\sum_{k=1}^{N}\left(L_i(z^{-1})u_i(k)-C_i(z^{-1},\theta_i)L_i(z^{-1})e_i(k)\right)^2 \quad (2)$$

$$e_i(k) = \bar{r}_i(k) - d_i y_i(k) \quad (3)$$

$$\bar{r}_i(k) = \frac{1}{M_i(z^{-1})}y_i(k), \quad (4)$$

where $\bar{r}_i(k)$ is the virtual reference input and $L_i(z^{-1})$ is a filter to be designed. Since $J_{iVR}(\theta_i)$ is convex with respect to θ_i, an optimal solution can be obtained. However, if the equivalent of $J_{iMR}(\theta_i)$ and $J_{iVR}(\theta_i)$ is not guaranteed, the obtained solution may not minimize $J_{iMR}(\theta_i)$. The problem is resolved by using $L_i(z^{-1})$.
Comparing $J_{iMR}(\theta_i)$ and $J_{iVR}(\theta_i)$ in the frequency domain, these are equivalent when the next conditions is satisfied:

$$|L_i|^2 = \frac{|M_i|^2|W_i|^2}{|1+d_iP_iC_i(\theta_i)|^2}\frac{1}{\Phi_{u_i}}, \quad (5)$$

where $z^{-1}=e^{-j\omega}$ is omitted. It is assumed that $|1+d_iP_iC_i(\theta_i)|^2 \cong |1+d_iP_iC_{i0}|$ when $J_{iMR}(\theta_i)$ is minimized by θ_i, where C_{i0} is an ideal controller that satisfies the next equation:

$$M_i = \frac{P_iC_{i0}}{1+d_iP_iC_{i0}}. \quad (6)$$

This equation is rewritten as follows:

$$1-d_iM_i = \frac{1}{1+d_iPC_{i0}}. \quad (7)$$

As a result, the filter is designed so as to satisfy the next equation:

$$|L_i|^2 = |1-d_iM_i|^2|M_i|^2|W_i|^2\Phi_{u_i}^{-1}. \quad (8)$$

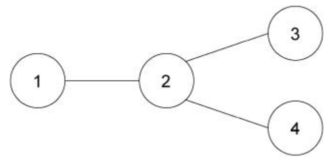


Fig. 2 Graph structure of a multi-agent system

3. Simulation

The graph structure an undirected graph as shown in Fig. 2. The dynamics of the agents are shown as follows:

$$P_1(s) = \frac{3}{s^2+s+2} \quad (9)$$

$$P_2(s) = \frac{3.5}{s^2+1.5s+2.5} \quad (10)$$

$$P_3(s) = \frac{4}{s^2+2s+3} \quad (11)$$

$$P_4(s) = \frac{4.5}{s^2+2.5s+3.5}. \quad (12)$$

The discrete-time period T_s is 1[s], and the control law of agent i is given as follows:

$$u_i(k) = \left(K_{Pi}+K_{Ii}\frac{T_s}{1-z^{-1}}+K_{Di}\frac{1-z^{-1}}{T_s}\right)e_i(k) \quad (13)$$

$$e_i(k) = r_i(k) - y_i(k) \quad (14)$$

$$(i = 1,\cdots,4),$$

where K_{Pi}, K_{Ii}, and K_{Di} are proportional, integral, and derivative gains, respectively and are determined directly from input/output data. Fig. 3 shows the response of agent 1 when white Gaussian noise with variance 1 is applied. White noise is also applied to other agents to obtain response data. Based on the corrected data, the controller parameters are determined by minimizing eq. (2). The obtained controller parameters are shown in Table 1, where the reference model is designed as follows:

$$M_i(s) = \frac{1}{d_i}M(s) \quad (15)$$

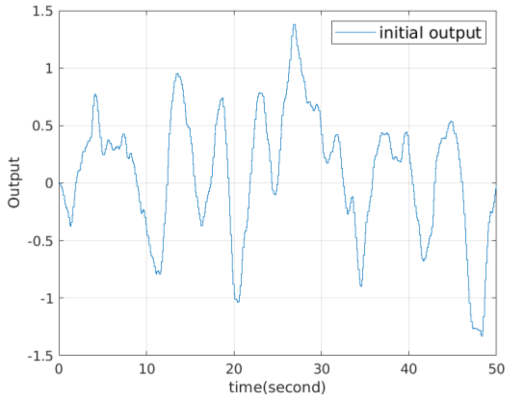
$$M(s) = \frac{1}{s+1}, \qquad (16)$$

where $d_1 = d_3 = d_4 = 1$ and $d_2 = 3$.

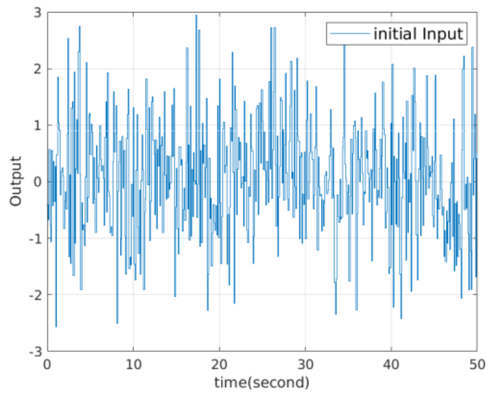
Table 1 PID parameters

	K_{Pi}	K_{Ii}	K_{Di}
θ_1	0.2265	0.6363	0.3204
θ_2	0.1045	0.2271	0.0916
θ_3	0.3727	0.7162	0.2417
θ_4	0.4412	0.7454	0.2154

Fig. 4 shows the simulation result of consensus control using the obtained PID parameters. It can be seen that all agents stably converge to a consensus value.



(a) Output



(b) Input

Fig. 3 Trajectories of initial input/output data

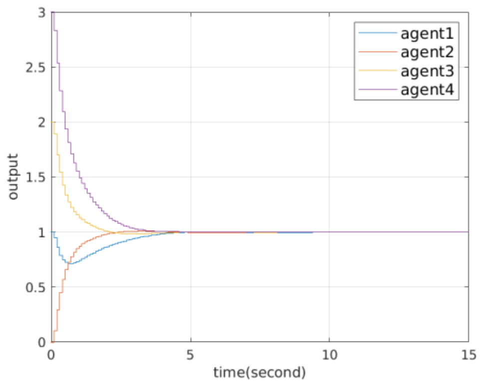


Fig. 4 Trajectories of consensus control

4. Conclusion

The present study has proposed a data-driven design for multi-agent systems. Therefore, even when the dynamic characteristics of agents are unknown, the controller parameters are determined directly from input/output data.

References

1. S. Azuma and M. Nagahara (Eds.): Control of Multi-agent Systems, CORONA Publishing (2015) (in Japanese).
2. X. Bu, Z. Hou, and H. Zhang: Data-driven multiagent systems consensus tracking using model free adaptive control, IEEE Trans. Neural Netw. Learn. Syst., 2018, 29(5): 1514-1524.
3. M. C. Campi, A. Lecchini and S. M. Savaresi: Virtual Reference Feedback Tuning (VRFT): direct method for the design of feedback controllers, Automatica, 2002, 38(8): 1337-1346.

Authors Introduction

Mr. Kenta Nagao

He received his Bachelor of Engineering from the School of Engineering, University of Hyogo, Japan in 2022 Currently, he is a graduate school student in University of Hyogo, Japan. His research interest includes data-driven control and multi-agent systems.

Dr. Natsuki Kawaguchi

He received a D.Eng. degree from University of Hyogo in 2018. He is an assistant professor in the Graduate School of Engineering at University of Hyogo, Japan. His research interests are fault detection and fault tolerant control.

Prof. Takao Sato

He received B.Eng. and M.Eng. degrees from Okayama University in 1997 and 1999, respectively, and a D.Eng. degree from Okayama University in 2002. He is a professor in the Graduate School of Engineering at University of Hyogo. His research interests are PID control, mechanical systems and multi-rate control.