

Sampled-Data Observer-Based Decentralized Fuzzy Control for Nonlinear Large-Scale Systems

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Abstract – In this paper, a sampled-data observer-based decentralized fuzzy control technique is proposed for a class of nonlinear large-scale systems, which can be represented to a Takagi-Sugeno fuzzy system. The premise variable is assumed to be measurable for the design of the observer-based fuzzy controller, and the closed-loop system is obtained. Based on an exact discretized model of the closed-loop system, the stability condition is derived for the closed-loop system. Also, the stability condition is converted into the linear matrix inequality (LMI) format. Finally, an example is provided to verify the effectiveness of the proposed techniques.

Keywords: Sampled-data observer-based decentralized fuzzy control, Nonlinear large-scale systems, Takagi-Sugeno fuzzy system, Exact discretized model, Linear matrix inequality

1. Introduction

Recently, as network-based systems are more increased in many engineering applications, such as wireless sensor networks, smart spaces and wide-area power systems, large-scale sampled-data systems, which well-represent characteristics of a network-based system, have attracted much attention [1, 2]. First, in the case of the large-scale system, due to the interconnection among subsystems, various problems are encountered, such as the high dimensionality and the structure constraint of the controller. To control a large-scale system, the decentralized control technique is more suitable than the traditional centralized control one. Thus, many decentralized control techniques have been proposed [3-7]; the decentralized fuzzy control technique [12-15] using a Takagi-Sugeno (T-S) fuzzy model has been recognized as one of the predominant decentralized control methods.

Apart from the large-scale system issue, the sampled-data control system has both a continuous-time plant and a discrete-time controller. In the case of linear systems, because the exact discretization of the continuous-time plant is possible, the sampled-data controller design is not difficult. However, in the case of nonlinear systems, the exact discretization is not possible, and so, to overcome this problem, various nonlinear sampled-data control techniques have been proposed, such as the Euler approximation [8, 9] and the conversion to an input delay controller [10, 11]. Sampled-data fuzzy control techniques, which are combination of the sampled-data control technique and the

T-S fuzzy model, have also been proposed in many studies [16-27] and are categorized into the input delay conversion approach and the direct discrete-time design approach.

First, the input delay conversion approach is to convert a sampled-data fuzzy controller into a continuous-time fuzzy one with the input time delay. This approach has been used in many studies [16-19], with such methods as H_∞ control [18] and robust control [19]. However, there are few studies about observer-based control or decentralized control in the input delay conversion approach. The direct discrete-time design approach [20-27] is to guarantee stability using the discretized model of the continuous-time plant. In [20-22], various sampled-data fuzzy control techniques using the direct discrete-time design approach have been proposed, such as the observer-based output-feedback scheme [20] and the robust control [21]. However, these studies did not address the problem of discretized errors. To conquer this problem, the analysis of the stability of the discrete-time model considering the discretized error and the limitation analysis of stability for the approximately discretized model have been studied in [23, 24]. In [25], by using the exact discretized model, a sampled-data fuzzy controller was designed for stabilization of the nonlinear system. The methodology of [25] was extended to the observer-based output-feedback scheme [26] and the guaranteed cost control technique [27], but the sampled-data decentralized fuzzy control problem has not been studied yet. Thus, there still remain sampled-data fuzzy control issues for the decentralized and the observer-based output-feedback approaches.

Motivated by the aforementioned analysis, this paper presents the sampled-data observer-based decentralized fuzzy control technique for a nonlinear large-scale system. Using the T-S fuzzy model, the nonlinear large-scale system is represented as a fuzzy large-scale system, and the observer-based controller is assumed to have the measurable

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premise variable. Based on the exact discretized model and the discrete-time Lyapunov functional, the sufficient condition of the stabilization is investigated for closed-loop system. Also, the stability condition is converted into linear matrix inequality (LMI) formats [32-36]. Finally, by the example, the validity of the proposed ideas, techniques, and procedures is shown.

Notation: The subscripts i and j denote the fuzzy rule indices and the subscripts k and l denote the subsystem indices. The notation $(\cdot)^T$ and $*$ are used for the transpose of the argument and the transposed element in symmetric positions, respectively. The notation $\sum_{l \neq k}^q$ means $\sum_{l=1, l \neq k}^q$.

2. Preliminaries

Consider a T-S fuzzy large-scale system consisting of q subsystems. Then, the i th IF-THEN rule of the k th subsystem is represented by the following form:

$$R_i^k : \text{IF } z_{k_1} \text{ is } \Gamma_{11}^k \text{ and ... and } z_{k_p} \text{ is } \Gamma_{ip}^k, \\ \text{THEN} \begin{cases} \dot{x}_k(t) = A_i^k x_k(t) + B_i^k u_k(t) + \sum_{l \neq k}^q A_i^{kl} x_l(t) \\ y_k(t) = y_k(nT) = C_i^k x_k(nT) \end{cases} \quad (1)$$

where z_{k_m} , $m \in \mathcal{I}_p$ is the premise variable; $x_k \in \mathbb{R}^{p_k}$ is the state variable; $u_k \in \mathbb{R}^{p_k}$ is the control input variable; $y_k \in \mathbb{R}^{q_k}$ is the sampled-data output variable to be determined in the time interval $t \in [nT, nT+T]$, $k \in \mathbb{Z}_{\geq 0}$; Γ_{im}^k , $(i, m, k) \in \mathcal{I}_r \times \mathcal{I}_p \times \mathcal{I}_q$, is a fuzzy set for z_{k_m} ; A_i^k , B_i^k and C_i^k denote nominal system matrices with appropriate dimensions for the i th rule of the k th subsystem; and A_i^{kl} is the interconnection matrix between the k th and the l th subsystems.

By applying the center-average defuzzification, product inference, and singleton fuzzifier into the fuzzy IF-THEN rule (1), the k th subsystem of the nonlinear large-scale system can be inferred as follows:

$$\dot{x}_k(t) = \sum_{i=1}^r \mu_i^k(z_k(t)) \left(A_i^k x_k(t) + B_i^k u_k(t) + \sum_{l \neq k}^q A_i^{kl} x_l(t) \right) \\ y_k(t) = y_k(nT) = \sum_{i=1}^r \mu_i^k(z_k(nT)) C_i^k x_k(nT) \quad (2)$$

where

$$\mu_i^k(z_k(t)) = \omega_i^k(z_k(t)) / \sum_{i=1}^r \omega_i^k(z_k(t)),$$

$$\omega_i^k(z_k(t)) = \prod_{m=1}^p \Gamma_{im}^k(z_m(t))$$

in which $\Gamma_{im}^k(z_m(t))$ is the fuzzy membership grade of z_{k_m} in Γ_{im}^k .

Assumption 1: The state variable $x_k(t)$ is not measurable, but the premise variable $z_k(t)$ is measurable in the continuous-time sense and the output variable $y_k(t)$ is measurable only at sampling instants.

Depending on Assumption 1, we consider the following sampled-data observer-based decentralized fuzzy controller:

$$\begin{aligned} \dot{\hat{x}}_k(t) &= \sum_{i=1}^r \mu_i^k(z_k(t)) \left(A_i^k \hat{x}_k(t) + B_i^k u_k(t) + L_i^k(y_k(t) - \hat{y}_k(t)) \right) \\ &=: A^k(t) \hat{x}_k(t) + B^k(t) u_k(t) + L^k(t)(y_k(t) - \hat{y}_k(t)) \\ \hat{y}_k(t) &= \hat{y}_k(nT) = \sum_{i=1}^r \mu_i^k(z_k(nT)) C_i^k \hat{x}_k(nT) =: C^k(nT) \hat{x}_k(nT) \\ u_k(t) &= u_k(nT) = \sum_{i=1}^r \mu_i^k(z_k(nT)) K_i^k \hat{x}_k(nT) =: K^k(nT) \hat{x}_k(nT) \end{aligned} \quad (3)$$

where $\hat{x}_k(t)$ is the state variable by the fuzzy observer, respectively; $\hat{y}_k(t)$ is the observer output; and K_i^k and L_i^k denote the control and observer gains.

To represent the closed-loop system with the sampled-data observer-based decentralized fuzzy controller, we suppose the estimation error $e_k(t) = x_k(t) - \hat{x}_k(t)$. Then, substituting (3) into (2) and the time derivative of $e_k(t)$, the k th sub-closed-loop system can be established as follows:

$$\dot{\chi}_k(t) = \Phi^k(t) \chi_k(nT) + \Lambda^k(t) \tilde{\chi}_k(t) + \sum_{l \neq k}^q \tilde{A}^{kl}(t) x_l(t) \quad (4)$$

where

$$\begin{aligned} \chi_k(t) &= \begin{bmatrix} x_k(t) \\ e_k(t) \end{bmatrix}, \quad \tilde{\chi}_k(t) = \chi_k(t) - \chi_k(nT), \\ \Phi^k(t) &= \begin{bmatrix} A^k(t) + B^k(t)K^k(nT) & -B^k(t)K^k(nT) \\ 0 & A^k(t) + L^k(t)C^k(nT) \end{bmatrix}, \\ \Lambda^k(t) &= \begin{bmatrix} A^k(t) & 0 \\ 0 & A^k(t) \end{bmatrix}, \quad \tilde{A}^{kl}(t) = \begin{bmatrix} A^{kl}(t) \\ A^{kl}(t) \end{bmatrix}. \end{aligned}$$

From the k th sub-closed-loop system (4), the observer-based decentralized fuzzy control problem can be stated as follows:

Problem 1: Find the fuzzy observer and control gain matrices L_i^k and K_i^k stabilizing the whole closed-loop large-scale system, which are respectively composed of sub-closed-loop systems with the sampled-data observer-based decentralized fuzzy controller.

3. Main Results

Before proceeding to the main results, the following lemmas and propositions will be needed throughout the

proof:

Lemma 1 [28]: Given any function vector x , matrix $P = P^T \succ 0$, and $t_0, t_f \in \mathbb{R}$ with $t_0 < t_f$, we have

$$\left(\int_{t_0}^{t_f} x(\tau) d\tau \right)^T P \left(\int_{t_0}^{t_f} x(\tau) d\tau \right) \leq (t_f - t_0) \int_{t_0}^{t_f} x(\tau)^T P x(\tau) d\tau.$$

Lemma 2 [27]: Suppose the nonlinear system such as $\dot{x} = f(t, x)$, where $f: [nT, nT+T] \times \mathbb{R}^q$ is piecewise continuous in t and locally Lipschitz in x and the matrix $P = P^T \succ 0$, then the following inequality is always satisfied

$$\int_{nT}^{nT+T} (x(t) - x(nT))^T P (x(t) - x(nT)) dt \leq T^2 \int_{nT}^{nT+T} \dot{x}(t)^T P \dot{x}(t) dt.$$

Lemma 3 [29]: Given any matrices Y and $P = P^T \succ 0$, we have

$$-Y^T P^{-1} Y \leq P - Y^T - Y.$$

Proposition 1: In the closed-loop system (4), there exists some constant $\rho > 0$ such that

$$\sum_{k=1}^q \|x_k(t)\| \leq \rho \sum_{k=1}^q \|\chi_k(nT)\| \quad (5)$$

for $t \in [nT, nT+T]$.

Proof: From the closed-loop system (4), we have

$$\begin{aligned} \dot{x}_k(t) &= A^k(t)x_k(t) + B^k(t)K^k(nT)x_k(nT) \\ &\quad - B^k(t)K^k(nT)e_k(nT) + \sum_{l \neq k}^q A^{kl}(t)x_l(t) \end{aligned} \quad (6)$$

Integrating from nT to t , taking the norm and summing all subsystems on both sides of equation (6) yields

$$\begin{aligned} &\sum_{k=1}^q \|x_k(t)\| \\ &\leq \sum_{k=1}^q \|x_k(nT)\| + \sum_{k=1}^q \left\| \int_{nT}^t (A^k(\tau)x_k(\tau) + B^k(\tau)K^k(nT)x_k(nT) \right. \\ &\quad \left. - B^k(\tau)K^k(nT)e_k(nT) + \sum_{l \neq k}^q A^{kl}(\tau)x_l(\tau)) d\tau \right\| \\ &\leq \sum_{k=1}^q \|x_k(nT)\| + \sum_{k=1}^q \int_{nT}^t a\|x_k(\tau)\| + b\|x_k(nT)\| \\ &\quad + b\|e_k(nT)\| + c \sum_{l \neq k}^q \|x_l(\tau)\| d\tau \end{aligned} \quad (7)$$

where

$$a = \sup_{(k,i) \in \mathcal{I}_q \times \mathcal{I}_r} \|A_i^k\|, \quad b = \sup_{(k,i,j) \in \mathcal{I}_q \times \mathcal{I}_r \times \mathcal{I}_r} \|B_i^k K_j^k\|,$$

$$c = \sup_{(k,l,i) \in \mathcal{I}_q \times \mathcal{I}_w \times \mathcal{I}_r} \|A_i^{kl}\|$$

and $\mathcal{I}_q \times \mathcal{I}_w$ denotes all pairs $(k,i) \in \mathcal{I}_q \times \mathcal{I}_q$ such that $k \neq l$.

By $\sum_{k=1}^q \sum_{l \neq k}^q x_l(t) = (q-1) \sum_{k=1}^q x_k(t)$, inequality (7) can be further developed as follows:

$$\begin{aligned} \sum_{k=1}^q \|x_k(t)\| &\leq \sum_{k=1}^q ((1+Tb)\|x_k(nT)\| + Tb\|e_k(nT)\|) \\ &\quad + (a + (q-1)c) \int_{nT}^t \sum_{k=1}^q \|x_k(\tau)\| d\tau \\ &\leq \sqrt{(1+Tb)^2 + (Tb)^2} \sum_{k=1}^q \|\chi_k(nT)\| \\ &\quad + (a + (q-1)c) \int_{nT}^t \sum_{k=1}^q \|x_k(\tau)\| d\tau \end{aligned}.$$

Then, an application of the Gronwall-Bellman inequality to $\sum_{k=1}^q \|x_k(t)\|$ results in

$$\begin{aligned} &\sum_{k=1}^q \|x_k(t)\| \\ &\leq \sqrt{(1+Tb)^2 + (Tb)^2} \exp((a + (q-1)c)t) \sum_{k=1}^q \|\chi_k(nT)\| \\ &= \rho \sum_{k=1}^q \|\chi_k(nT)\|. \end{aligned}$$

Remark 1: Proposition 1 shows the relation between $\sum_{k=1}^q \|x_k(t)\|$ and $\sum_{k=1}^q \|x_k(nT)\|$ for the closed-loop system (4). By Proposition 1, we know that each state variable $x_k(t)$ converges to the origin when the whole $x_k(nT)$ converges to the origin.

The sufficient condition for stability of the closed-loop system (4) is summarized as the following proposition:

Proposition 2: If there exist some symmetric and positive definite matrices P_1^k, P_2^k, P_3^k and some matrices K_i^k, L_i^k such that the following inequality is satisfied, then the whole closed-loop system which is composed of sub-closed-loop systems (4) is asymptotically stable.

$$\begin{bmatrix} -T^{-1}\omega P_1^k + \tilde{P}_3^k & * & * & * & * \\ \tilde{P}_3^k & -P_2^k + \tilde{P}_3^k & * & * & * \\ 0 & 0 & -P_3^k & * & * \\ \omega \Psi^k(t) & \omega \Lambda^k(t) & \tilde{A}^k(t) & -T^{-1}\omega (P_1^k)^{-1} & * \\ \omega \Psi^k(t) & \omega \Lambda^k(t) & \tilde{A}^k(t) & 0 & -T^{-2}\omega^2 (P_2^k)^{-1} \end{bmatrix} \prec 0$$

$$(k, l) \in \mathcal{I}_q \times \mathcal{I}_w \quad (8)$$

where, $\tilde{P}_3^k = \text{diag}\{P_3^k, 0\}$, $\Psi^k(t) = T^{-1}I + \Phi^k(t)$, $\omega = (q-1)^{-1}$

for $t \in [nT, nT+T]$.

Proof: By integrating the closed-loop system (4) from nT to $nT+T$, we have the exact discretized model as follows:

$$\begin{aligned} & \chi_k(nT+T) \\ &= \chi_k(nT) + \int_{nT}^{nT+T} \left(\Phi^k(t)\chi_k(nT) + \Lambda^k(t)\tilde{\chi}_k(t) + \sum_{l \neq k}^q \tilde{A}^{kl}(t)x_l(t) \right) dt \end{aligned} \quad (9)$$

Based on the discretized model (9), we consider the discrete-time Lyapunov function candidate as follows:

$$V = \sum_{k=1}^q V_k(\chi_k(nT)) = \sum_{k=1}^q \chi_k(nT)^T P_1^k \chi_k(nT).$$

where $P_1^k = (P_1^k)^T \succ 0$, then the first forward difference of V can be defined by

$$\Delta V = \sum_{k=1}^q \left(\chi_k(nT+T)^T P_1^k \chi_k(nT+T) - \chi_k(nT)^T P_1^k \chi_k(nT) \right). \quad (10)$$

Substituting (9) into (10) yields

$$\begin{aligned} \Delta V &= \sum_{k=1}^q \left(\chi_k(nT) + \int_{nT}^{nT+T} \left(\Phi^k(t)\chi_k(nT) + \Lambda^k(t)\tilde{\chi}_k(t) \right. \right. \\ &\quad \left. \left. + \sum_{l \neq k}^q \tilde{A}^{kl}(t)x_l(t) \right) dt \right)^T P_1^k \\ &\quad \times \left(\chi_k(nT) + \int_{nT}^{nT+T} \left(\Phi^k(t)\chi_k(nT) + \Lambda^k(t)\tilde{\chi}_k(t) \right. \right. \\ &\quad \left. \left. + \sum_{l \neq k}^q \tilde{A}^{kl}(t)x_l(t) \right) dt \right) - \sum_{k=1}^q \chi_k(nT)^T P_1^k \chi_k(nT) \\ &= \sum_{k=1}^q \left(\int_{nT}^{nT+T} \left(\Psi^k(t)\chi_k(nT) + \Lambda^k(t)\tilde{\chi}_k(t) + \sum_{l \neq k}^q \tilde{A}^{kl}(t)x_l(t) \right) dt \right)^T \\ &\quad \times P_1^k \left(\int_{nT}^{nT+T} \left(\Psi^k(t)\chi_k(nT) + \Lambda^k(t)\tilde{\chi}_k(t) + \sum_{l \neq k}^q \tilde{A}^{kl}(t)x_l(t) \right) dt \right) \\ &\quad - \sum_{k=1}^q \chi_k(nT)^T P_1^k \chi_k(nT). \end{aligned} \quad (11)$$

By applying Lemma 1 and 2, equation (11) becomes

$$\begin{aligned} \Delta V &= \sum_{k=1}^q \int_{nT}^{nT+T} \left(\Psi^k(t)\chi_k(nT) + \Lambda^k(t)\tilde{\chi}_k(t) + \sum_{l \neq k}^q \tilde{A}^{kl}(t)x_l(t) \right)^T \\ &\quad \times T P_1^k \left(\Psi^k(t)\chi_k(nT) + \Lambda^k(t)\tilde{\chi}_k(t) + \sum_{l \neq k}^q \tilde{A}^{kl}(t)x_l(t) \right) dt \\ &\quad - \sum_{k=1}^q \chi_k(nT)^T P_1^k \chi_k(nT) \end{aligned}$$

$$\begin{aligned} &+ \sum_{k=1}^q \sum_{l \neq k}^q \int_{nT}^{nT+T} \left(\Psi^k(t)\chi_k(nT) + \Lambda^k(t)\tilde{\chi}_k(t) + \sum_{l \neq k}^q \tilde{A}^{kl}(t)x_l(t) \right)^T \\ &\quad \times T^2 P_2^k \left(\Psi^k(t)\chi_k(nT) + \Lambda^k(t)\tilde{\chi}_k(t) + \sum_{l \neq k}^q \tilde{A}^{kl}(t)x_l(t) \right) dt \\ &- \sum_{k=1}^q \sum_{l \neq k}^q \int_{nT}^{nT+T} \tilde{\chi}_k(t)^T P_2^k \tilde{\chi}_k(t) dt \end{aligned} \quad (12)$$

where $P_2^k = (P_2^k)^T \succ 0$.

For the positive definite matrices P_1^k and P_3^k , the followings are satisfied

$$\begin{aligned} & \sum_{k=1}^q \left(\sum_{l \neq k}^q \tilde{A}^{kl}(t)x_l(t) \right)^T P_1^k \left(\sum_{l \neq k}^q \tilde{A}^{kl}(t)x_l(t) \right) \\ & \leq (q-1) \sum_{k=1}^q \sum_{l \neq k}^q \left(\tilde{A}^{kl}(t)x_l(t) \right)^T P_1^k \tilde{A}^{kl}(t)x_l(t). \end{aligned} \quad (13)$$

$$\sum_{k=1}^q \sum_{l \neq k}^q \int_{nT}^{nT+T} x_k(t)^T P_3^k x_k(t) dt = \sum_{k=1}^q \sum_{l \neq k}^q \int_{nT}^{nT+T} x_l(t)^T P_3^k x_l(t) dt \quad (14)$$

By applying (13) and (14) to (12), we have

$$\begin{aligned} \Delta V &\leq \sum_{k=1}^q \sum_{l \neq k}^q \int_{nT}^{nT+T} \left(\omega \Psi^k(t)\chi_k(nT) + \omega \Lambda^k(t)\tilde{\chi}_k(t) + \tilde{A}^{kl}(t)x_l(t) \right)^T \\ &\quad \times T \omega^{-1} P_1^k \left(\omega \Psi^k(t)\chi_k(nT) + \omega \Lambda^k(t)\tilde{\chi}_k(t) + \tilde{A}^{kl}(t)x_l(t) \right) dt \\ &\quad - \sum_{k=1}^q \sum_{l \neq k}^q \int_{nT}^{nT+T} T^{-1} \omega \chi_k(nT)^T P_1^k \chi_k(nT) dt \\ &\quad + \sum_{k=1}^q \sum_{l \neq k}^q \int_{nT}^{nT+T} \left(\omega \Psi^k(t)\chi_k(nT) + \omega \Lambda^k(t)\tilde{\chi}_k(t) + \tilde{A}^{kl}(t)x_l(t) \right)^T \\ &\quad \times T^2 \omega^{-2} P_2^k \left(\omega \Psi^k(t)\chi_k(nT) + \omega \Lambda^k(t)\tilde{\chi}_k(t) + \tilde{A}^{kl}(t)x_l(t) \right) dt \\ &\quad - \sum_{k=1}^q \sum_{l \neq k}^q \int_{nT}^{nT+T} \tilde{\chi}_k(t)^T P_2^k \tilde{\chi}_k(t) dt \\ &\quad + \sum_{k=1}^q \sum_{l \neq k}^q \int_{nT}^{nT+T} \left(\chi_k(nT) + \tilde{\chi}_k(t) \right)^T \tilde{P}_3^k \left(\chi_k(nT) + \tilde{\chi}_k(t) \right) dt \\ &\quad - \sum_{k=1}^q \sum_{l \neq k}^q \int_{nT}^{nT+T} x_l(t)^T P_3^k x_l(t) dt \\ &= \sum_{k=1}^q \sum_{l \neq k}^q \int_{nT}^{nT+T} \begin{bmatrix} \chi_k(nT) \\ \tilde{\chi}_k(t) \\ x_l(t) \end{bmatrix}^T \mathcal{P}^{kl} \begin{bmatrix} \chi_k(nT) \\ \tilde{\chi}_k(t) \\ x_l(t) \end{bmatrix} dt \\ &\quad + \sum_{k=1}^q \sum_{l \neq k}^q \int_{nT}^{nT+T} \begin{bmatrix} \chi_k(nT) \\ \tilde{\chi}_k(t) \\ x_l(t) \end{bmatrix}^T \begin{bmatrix} \omega \Psi^k(t) & \omega \Lambda^k(t) & \tilde{A}^{kl}(t) \end{bmatrix} \\ &\quad \times \left(T \omega^{-1} P_1^k + T^2 \omega^{-2} P_2^k \right) \begin{bmatrix} \omega \Psi^k(t) & \omega \Lambda^k(t) & \tilde{A}^{kl}(t) \end{bmatrix} \begin{bmatrix} \chi_k(nT) \\ \tilde{\chi}_k(t) \\ x_l(t) \end{bmatrix} dt \end{aligned} \quad (15)$$

where

$$\mathcal{P}^{kl} = \begin{bmatrix} -T^{-1}\omega P_1^k + \tilde{P}_3^k & * & * \\ \tilde{P}_3^k & -P_2^k + \tilde{P}_3^k & * \\ 0 & 0 & -P_3^l \end{bmatrix}.$$

Thus, from inequality (15), if the following inequality is satisfied

$$\mathcal{P}^{kl} + \begin{bmatrix} \omega\Psi^k(t) & \omega\Lambda^k(t) & \tilde{A}^{kl}(t) \end{bmatrix}^T \times (T\omega^{-1}P_1^k + T^2\omega^{-2}P_2^k) \begin{bmatrix} \omega\Psi^k(t) & \omega\Lambda^k(t) & \tilde{A}^{kl}(t) \end{bmatrix} \prec 0 \quad (16)$$

then the ΔV is less than 0.

By using the Schur complement in (16), we can obtain inequality (8). Thus, if inequality (8) is satisfied, the equilibrium point $x_k(nT)=0$ of all discretized sub-closed-loop systems (9) is asymptotically stable. Also, by Proposition 1, the equilibrium point $x_k(t)=0$ of all sub-closed-loop systems (4) is also asymptotically stable. ■

By Proposition 2, we have the stabilization condition of the nonlinear large-scale system (2) with the sampled-data observer-based decentralized fuzzy controller. However, it is difficult to directly solve inequality (8) and obtain the gain matrices K_i^k and L_i^k . Thus, to convert into LMI format, which is easily solved by a convex optimization toolbox, we respectively define the matrices P_1^k and P_2^k without the loss of generality as follows:

$$P_1^k = \text{diag}\{P_{11}^k, P_{12}^k\} \quad (17)$$

$$P_2^k = \text{diag}\{P_{21}^k, \alpha_k P_{12}^k\}. \quad (18)$$

where $\alpha_k > 0$ is a given constant scalar.

Based on the newly defined matrices P_1^k , P_2^k and Proposition 2, we summarize the LMI condition satisfying inequality (8).

Theorem 1: If there exist some symmetric and positive matrices Q_1^k , Q_2^k , Q_3^k , P_{12}^k , some symmetric matrices R_1^k , R_2^k , R_3^k , and some matrices M_i^k , N_i^k , such that the following LMIs are satisfied, then inequality (8) is also satisfied and the whole closed-loop system (4) is asymptotically stable.

$$\mathcal{X}_{ij}^{kl} \prec 0 \quad (k, l, i, j) \in \mathcal{I}_q \times \mathcal{I}_w \times \mathcal{I}_r \times \mathcal{I}_r \quad (19)$$

$$\begin{bmatrix} Y_{ij}^k & * \\ J_i^k & J_2^k \end{bmatrix} \prec 0 \quad (k, i, j) \in \mathcal{I}_q \times \mathcal{I}_r \times \mathcal{I}_r \quad (20)$$

where

$$\mathcal{X}_{ij}^{kl} = \begin{bmatrix} G_1^{kl} & * & * \\ X_{ij}^{kl} & G_2^k & * \\ G_3^k & 0 & -Q_3^k \end{bmatrix},$$

$$\begin{aligned} G_1^k &= \text{diag}\{-T^{-1}\omega Q_1^k, -\beta_k Q_1^k, -Q_2^k, -R_1^k, -Q_3^k\}, \\ G_2^k &= \text{diag}\{-T^{-1}\omega Q_1^k, -R_2^k, -T^{-2}\omega^2 Q_2^k, -R_3^k\}, \\ G_3^k &= [Q_1^k \ 0 \ Q_2^k \ 0 \ 0], \\ X_{ij}^k &= \begin{bmatrix} \omega(T^{-1}Q_1^k + \Omega_{ij}^k) & -\omega B_i^k M_j^k & \omega A_i^k Q_2^k & 0 & A_i^{kl} Q_3^k \\ 0 & 0 & 0 & \omega A_i^k R_1^k & A_i^{kl} Q_3^k \\ \omega \Omega_{ij}^k & -\omega B_i^k M_j^k & \omega A_i^k Q_2^k & 0 & A_i^{kl} Q_3^k \\ 0 & 0 & 0 & \omega A_i^k R_1^k & A_i^{kl} Q_3^k \end{bmatrix}, \\ \Omega_{ij}^k &= A_i^k Q_1^k + B_i^k M_j^k, \\ Y_{ij}^k &= \begin{bmatrix} -T^{-1}\omega P_{12}^k & * & * & * \\ 0 & -\alpha_k P_{12}^k & * & * \\ \omega(T^{-1}P_{12}^k + P_{12}^k A_i^k - N_i^k C_j^k) & 0 & -T^{-1}\omega P_{12}^k & * \\ \omega(P_{12}^k A_i^k - N_i^k C_j^k) & 0 & 0 & -T^{-2}\omega^2 P_{12}^k \end{bmatrix}, \\ J_2^k &= \text{diag}\{I, I, \gamma_{1_k} P_{12}^k, \gamma_{2_k} P_{12}^k\}, \\ J_2^k &= \text{diag}\{-\beta_k^{-1} Q_1^k, -R_1^k, R_2^k - 2\gamma_{1_k} I, R_3^k - 2\gamma_{2_k} I\} \end{aligned}$$

and $\alpha_k > 0$, $\beta_k > 0$, $\gamma_{1_k} > 0$ and $\gamma_{2_k} > 0$ are given constant scalars.

Proof: By substituting (17) and (18) into inequality (8), we obtain

$$\begin{bmatrix} H_{11}^{kl} & * \\ H_{21}^{kl}(t) & H_{22}^k \end{bmatrix} \prec 0 \quad (21)$$

where

$$\begin{aligned} H_{11}^{kl} &= \begin{bmatrix} -T^{-1}\omega P_{11}^k + P_3^k & * & * & * & * \\ 0 & -T^{-1}\omega P_{12}^k & * & * & * \\ P_3^k & 0 & -P_{21}^k + P_3^k & * & * \\ 0 & 0 & 0 & -\alpha_k P_{12}^k & * \\ 0 & 0 & 0 & 0 & -P_3^l \end{bmatrix}, \\ H_{21}^{kl}(t) &= \begin{bmatrix} \omega(T^{-1}I + \Upsilon_1^k(t)) & -\omega B^k(t)K^k(nT) & \omega A^k(t) & 0 & A^{kl}(t) \\ 0 & \omega(T^{-1}I + \Upsilon_2^k(t)) & 0 & \omega A^k(t) & A^{kl}(t) \\ \omega \Upsilon_1^k(t) & -\omega B^k(t)K^k(nT) & \omega A^k(t) & 0 & A^{kl}(t) \\ 0 & \omega \Upsilon_2^k(t) & 0 & \omega A^k(t) & A^{kl}(t) \end{bmatrix}, \\ H_{22}^k &= \text{diag}\{-T^{-1}\omega(P_{11}^k)^{-1}, -T^{-1}\omega(P_{12}^k)^{-1}, \\ &\quad -T^{-2}\omega^2(P_{21}^k)^{-1}, -\alpha_k T^{-2}\omega^2(P_{12}^k)^{-1}\}, \\ \Upsilon_1^k(t) &= A^k(t) + B^k(t)K^k(nT), \quad \Upsilon_2^k(t) = A^k(t) - L^k(t)C^k(nT). \end{aligned}$$

If there exist symmetric matrices $(R_1^k)^{-1}$, R_2^k and R_3^k such that the following inequality is satisfied:

$$\begin{bmatrix} -T^{-1}\omega P_{12}^k & * & * & * \\ 0 & -\alpha_k P_{12}^k & * & * \\ \omega(T^{-1}I + \Upsilon_2^k(t)) & 0 & -T^{-1}\omega(P_{12}^k)^{-1} & * \\ \omega \Upsilon_2^k(t) & 0 & 0 & -T^{-2}\omega^2(P_{12}^k)^{-1} \end{bmatrix}$$

$$\prec \begin{bmatrix} -\beta_k P_{11}^k & * & * & * \\ 0 & -(R_1^k)^{-1} & * & * \\ 0 & 0 & -R_2^k & * \\ 0 & 0 & 0 & -R_3^k \end{bmatrix} \quad (22)$$

Then, inequality (21) is majorized by

$$\begin{bmatrix} \hat{H}_{11}^{kl} & * \\ \hat{H}_{21}^{kl}(t) & \hat{H}_{22}^k \end{bmatrix} \prec 0 \quad (23)$$

where

$$\begin{aligned} \hat{H}_{11}^{kl} &= \begin{bmatrix} -T^{-1}\omega P_{11}^k + P_3^k & * & * & * & * \\ 0 & -\beta_k P_{11}^k & * & * & * \\ P_3^k & 0 & -P_{21}^k + P_3^k & * & * \\ 0 & 0 & 0 & -(R_1^k)^{-1} & * \\ 0 & 0 & 0 & 0 & -P_3^l \end{bmatrix}, \\ \hat{H}_{21}^{kl}(t) &= \begin{bmatrix} \omega(T^{-1}I + Y_1^k(t)) - \omega B^k(t)K^k(nT) & \omega A^k(t) & 0 & A^{kl}(t) \\ 0 & 0 & 0 & \omega A^k(t)A^{kl}(t) \\ \omega Y_1^k(t) & -\omega B^k(t)K^k(nT) & \omega A^k(t) & 0 & A^{kl}(t) \\ 0 & 0 & 0 & \omega A^k(t) & A^{kl}(t) \end{bmatrix}, \\ \hat{H}_{22}^k &= \text{diag}\{-T^{-1}\omega(P_{11}^k)^{-1}, -R_2^k, -T^{-2}\omega^2(P_{21}^k)^{-1}, -R_3^k\}. \end{aligned}$$

By using the congruence transformation with $\text{diag}\{(P_{11}^k)^{-1}, (P_{11}^k)^{-1}, (P_{21}^k)^{-1}, (R_1^k)^{-1}, (R_3^k)^{-1}, I, I, I, I\}$, applying the Schur complement and denoting $(P_{11}^k)^{-1} = Q_1^k$, $(P_{21}^k)^{-1} = Q_2^k$, $(P_3^k)^{-1} = Q_3^k$, $K_i^k(P_{11}^k)^{-1} = M_i^k$, inequality (23) can be represented as

$$\sum_{i=1}^r \sum_{j=1}^r \mu_i^k(z_k(t)) \mu_j^k(z_k(nT)) \mathcal{X}_{ij}^{kl} \prec 0.$$

Also, by using the Schur complement, applying Lemma 3 and denoting $P_{12}^k L_i^k = N_i^k$, inequality (22) can be converted into LMI (20). Thus, if LMIs (19) and (20) are satisfied, inequality (8) of Proposition 2 is also satisfied, and the whole closed-loop system (4) is asymptotically stable. ■

Remark 2: In Theorems 1, we assume that the parameters α_k , β_k , γ_{1_k} and γ_{2_k} are given in advance. However, when these parameters are unknown, the parameter value must first be determined. In this case, the iterative LMI (ILMI), which is minutely described in [12], has to be used.

4. An illustrative example

In this section, an example is given to validate the

proposed sampled-data observer-based decentralized fuzzy control method. Suppose the double Chua's circuit system [30, 31] connected by a resistor as follows:

$$\begin{aligned} \dot{v}_{k_1}(t) &= \frac{1}{C_{k_1}} \left(\frac{1}{R_k} (v_{k_2}(t) - v_{k_1}(t)) - f_k(v_{k_1}(t)) + \frac{1}{R_a} (v_{k_1}(t) - v_{k_1}(t)) + u_{k_1}(t) \right) \\ \dot{v}_{k_2}(t) &= \frac{1}{C_{k_2}} \left(\frac{1}{R_k} (v_{k_1}(t) - v_{k_2}(t)) - i_k(t) + \sigma_{k_1} u_{k_2}(t) \right) \\ i_k(t) &= -\frac{1}{L_k} (v_{k_2}(t) + \sigma_{k_2} u_{k_3}(t)), \quad y_k(t) = y_k(nT) = v_{k_1}(nT), \end{aligned}$$

where $\{(k, l) \in \mathcal{Z}_2 \mid k \neq l\}$; $v_{k_1}(t)$, $v_{k_2}(t)$ and $i_k(t)$ are state variables of the k th Chua's circuit; R_k is a resistor with $R_1 = 100m\Omega$ and $R_2 = 125m\Omega$; C_{k_1} and C_{k_2} are capacitors with $C_{k_1} = 1F$ and $C_{k_2} = 10F$; L_k is an inductor with $L_1 = 70mH$ and $L_2 = 75mH$; σ_{k_1} and σ_{k_2} are input coefficients with $\sigma_{1_1} = 10$, $\sigma_{1_2} = 10$, $\sigma_{2_1} = 0.07$ and $\sigma_{2_2} = 0.075$; $R_a = 3\Omega$ is an interconnected resistor between circuits; and $f_k(v_{k_1}(t)) = (g_b/R_k)v_{k_1}(t) + ((g_a - g_b)/2R_k)(|v_{k_1}(t) + 1| - |v_{k_1}(t) - 1|)$ is a Chua's diode with $g_a = -1.27$ and $g_b = -0.68$.

By choosing $x_k(t) = [v_{k_1}(t) \ v_{k_2}(t) \ i_k(t)]^T$ and $u_k(t) = [u_{k_1}(t) \ u_{k_2}(t) \ u_{k_3}(t)]^T$, the T-S fuzzy system of the k th subsystem can be constructed as follows:

$$\begin{aligned} \dot{x}_k(t) &= \sum_{i=1}^2 \mu_i^k(x_{k_1}(t)) \left(A_i^k x_k(t) + B_i^k u_k(t) + \sum_{l \neq k}^2 A_l^{kl} x_l(t) \right) \\ y_k(t) &= y_k(nT) = \sum_{i=1}^2 \mu_i^k(x_{k_1}(nT)) C_i^k x_k(nT) \end{aligned}$$

where

$$\begin{aligned} A_1^k &= \begin{bmatrix} (d-1)\lambda_{k_1} - \lambda_{k_3} & \lambda_{k_1} & 0 \\ 1 & -1 & 1 \\ 0 & -\lambda_{k_2} & 0 \end{bmatrix}, \\ A_2^k &= \begin{bmatrix} -(d+1)\lambda_{k_1} - \lambda_{k_3} & \lambda_{k_1} & 0 \\ 1 & -1 & 1 \\ 0 & -\lambda_{k_2} & 0 \end{bmatrix}, \\ A_i^{kl} &= \begin{bmatrix} \lambda_{k_3} & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad B_i^k = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \\ C_i^k &= [1 \ 0 \ 0], \\ \mu_1^k(x_{k_1}(t)) &= \begin{cases} \frac{1}{2} \left(1 - (f_k(x_{k_1}(t))/dx_{k_1}(t)) \right), & x_{k_1}(t) \neq 0 \\ g_a & x_{k_1}(t) = 0 \end{cases} \\ \mu_2^k(x_{k_1}(t)) &= 1 - \mu_1^k(x_{k_1}(t)) \end{aligned}$$

with the parameters $\lambda_{1_1} = 10$, $\lambda_{1_2} = 14.2857$, $\lambda_{2_1} = 8$, $\lambda_{2_2} = 13.3333$, $\lambda_{3_1} = \lambda_{3_2} = 0.3333$ and $d = 1.8$ for

$(i, k, l) \in \mathcal{I}_2 \times \mathcal{I}_2 \times \mathcal{I}_2$ with $k \neq l$. In this simulation model, the premise variable $x_{k_l}(t)$ can be directly obtained by the output variable.

$$K_1^1 = \begin{bmatrix} -10.9105 & -9.0469 & 0.0099 \\ -2.6431 & -12.9171 & -0.8660 \\ 1.5916 & 12.7990 & -18.1612 \end{bmatrix},$$

$$K_2^1 = \begin{bmatrix} -10.9105 & -9.0469 & 0.0099 \\ -2.6431 & -12.9171 & -0.8660 \\ 1.5916 & 12.7990 & -18.1612 \end{bmatrix},$$

$$K_1^2 = \begin{bmatrix} -15.6162 & -7.1073 & 0.0049 \\ -4.5550 & -13.1838 & -0.7869 \\ 3.2756 & 11.3915 & -26.1455 \end{bmatrix},$$

$$K_2^2 = \begin{bmatrix} -15.6162 & -7.1073 & 0.0049 \\ -4.5550 & -13.1838 & -0.7869 \\ 3.2756 & 11.3915 & -26.1455 \end{bmatrix},$$

$$L_1^1 = \begin{bmatrix} 67.5308 \\ 49.9071 \\ -2.7486 \end{bmatrix}, \quad L_2^1 = \begin{bmatrix} 31.5308 \\ 49.9071 \\ -2.7486 \end{bmatrix},$$

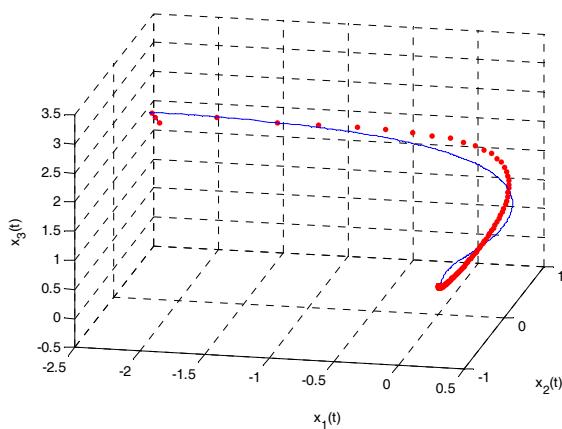


Fig. 1. The time response of large-scale system: subsystem 1 (solid) and subsystem 2 (dash-dotted).

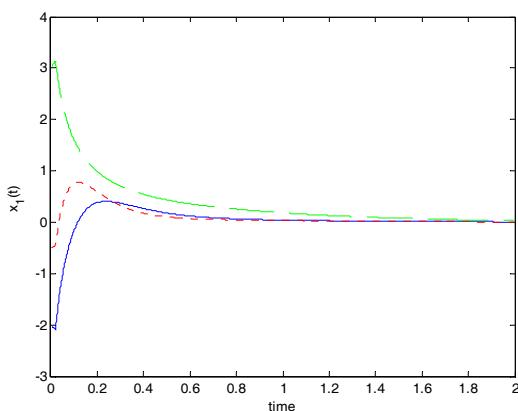


Fig. 2. The time response of subsystem 1 for $T = 0.02$ s: $x_{11}(t)$ (solid), $x_{12}(t)$ (dotted) and $x_{13}(t)$ (dashed).

$$L_1^2 = \begin{bmatrix} 62.4354 \\ 35.6605 \\ -4.2859 \end{bmatrix}, \quad L_2^2 = \begin{bmatrix} 32.0354 \\ 35.6605 \\ -4.2859 \end{bmatrix}.$$

Based on the above control and observer gains, we obtain the closed-loop large-scale systems and present the

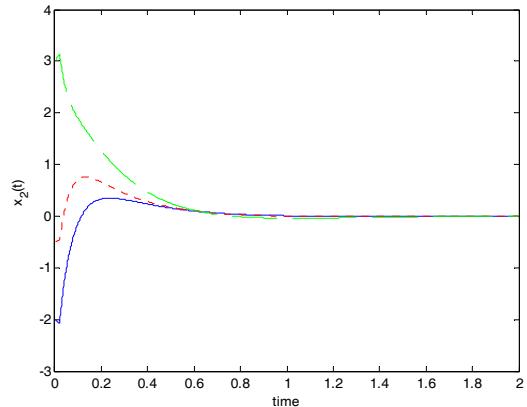


Fig. 3. The time response of subsystem 2 for $T = 0.02$ s: $x_{21}(t)$ (solid), $x_{22}(t)$ (dotted) and $x_{23}(t)$ (dashed).

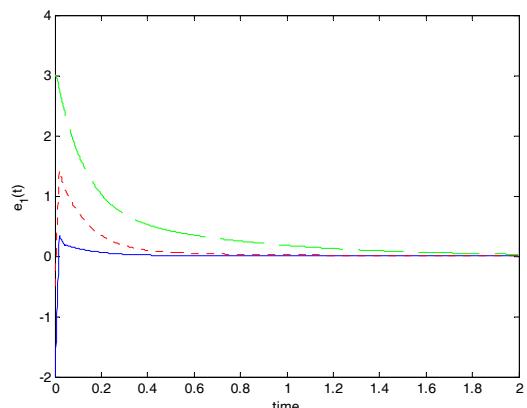


Fig. 4. The estimated error of subsystem 1 for $T = 0.02$ s: $e_{11}(t)$ (solid), $e_{12}(t)$ (dotted) and $e_{13}(t)$ (dashed).

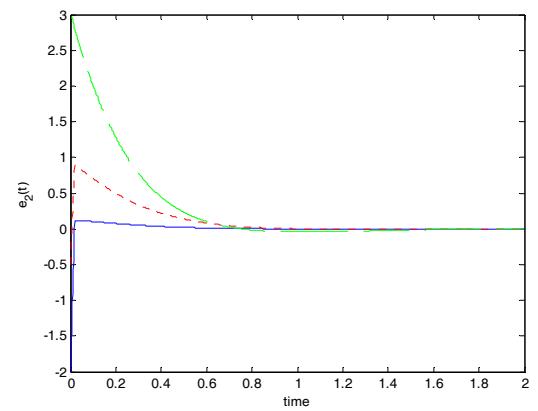


Fig. 5. The estimated error of subsystem 2 for $T = 0.02$ s: $e_{21}(t)$ (solid), $e_{22}(t)$ (dotted) and $e_{23}(t)$ (dashed).

time responses of the state variables and estimated errors for each subsystem. The time responses are shown in Figs. 1, 2, 3, 4 and 5. As shown in the figures, all state variables and errors are converted to 0, and it means that the obtained gains are suitable to stabilize the double Chua's circuit system. Thus, we know that the proposed sampled-data observer-based decentralized fuzzy control technique is suitable for a nonlinear large-scale system.

5. Conclusions

This paper has established a sampled-data observer-based decentralized fuzzy controller for nonlinear large-scale systems. Based on the T-S fuzzy system, the closed-loop systems have been represented. The sufficient condition has been derived for the stability of the closed-loop system by using the exact discretized model and the discrete-time Lyapunov functional and was formulated in the LMI formats. Finally, the numerical example was provided to demonstrate the effectiveness of the proposed techniques.

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