

Digital Controller Design for Fuzzy Systems with Packet Loss: Intelligent Digital Redesign Approach

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Abstract—In this paper, a novel digital controller is proposed for the nonlinear systems with packet loss using the intelligent digital redesign (IDR). For the fuzzy controller, the nonlinear system is represented by a Takagi–Sugeno (T–S) fuzzy model. The IDR technique is to convert a pre-designed analog controller into an equivalent digital controller. For this technique, the discretized models of the analog and digital closed-loop system are presented, respectively. The digital control gain is obtained to minimize the norm error between the state of the analog and digital closed-loop systems and stabilize the digital closed-loop system. Its sufficient conditions are derived in terms of linear matrix inequalities (LMIs). Finally, a numerical example is provided to verify the effectiveness of the proposed technique.

Index Terms—intelligent digital redesign (IDR), Takagi–Sugeno (T–S) fuzzy model, packet loss, linear matrix inequality (LMI)

I. INTRODUCTION

Networked control system (NCS) has been a very hot research topic over the past decade [1], [2], [3], [4], [5]. NCSs have attracted much attention because of their successful applications in modern complicated industry processes, e.g., aircraft and space shuttle, unclear power stations, high-performance automobiles, etc. Basically, NCS has wireless communication channels or networks between sensors, controllers, and actuators. Due to these structure, there are many problems, such as time delay, packet loss and so on. Also, the system is continuous, while the control law is discrete. For solving above problems, many studies were progressed. However, contrary to time delay and sampling study, there are not enough studies for packet loss problem. To solve the packet loss problem, it needs an stochastic approach.

Also, because of continuous system and discrete controller, the study for the digital control is essential for NCS. Among many digital control methods, a digital redesign (DR) is widely used as the predominant digital controller design technique [6], [7], [8]. It executes as a tool which converts an original analog controller into a new digital one maintaining the state-matching condition. However, there is a problem that the DR can be only used in linear systems.

In order to apply DR method in the nonlinear system, an intelligent digital redesign (IDR), which is merged with the

fuzzy control scheme and the DR method, was proposed in [9]. Also, the robust IDR problem was studied for nonlinear systems with parametric uncertainties [10]. However, these papers dealt with the local state-matching without concerning the global one. The global approaches of the IDR problem were presented in [11], [12], [13], but they did not consider the packet loss problem of the nonlinear systems. The stochastic stability for the nonlinear systems with packet loss were proposed in [3], [4], [5]. But there were no studies about the IDR problem for the nonlinear systems with packet loss.

In this paper, we propose a novel digital controller design for the nonlinear systems which can be modelled by T–S fuzzy systems. For the digital controller design, we use the IDR approach which is to convert a pre-designed analog controller into an equivalent digital one. To develop the IDR technique, the discretized models of the analog and digital closed-loop system with the decentralized controller are presented, respectively. Based on discretized models, sufficient conditions are achieved for both the state-matching condition between analog and digital closed-loop systems and the stability of the digital closed-loop system. Its constructive conditions are presented in terms of linear matrix inequalities (LMIs). Finally, it shows the validity of the proposed ideas, techniques and procedures, through simple example.

This paper is organized as follows: Section 2 describes the discretized models of the T–S fuzzy systems. The stability and state-matching conditions are proposed with the LMI form in Section 3. In Section 4, simulation example is provided to demonstrate the design procedures. Finally, the conclusions are given in Section 5.

II. PRELIMINARIES

Consider a T–S fuzzy system, in which the i th IF-THEN rule is represented by the following form:

$$\begin{aligned} R_i : & \text{IF } z_1(t) \text{ is } \Gamma_{i1} \text{ and } \cdots \text{ and } z_p(t) \text{ is } \Gamma_{ip} \\ & \text{THEN } \dot{x}(t) = A_i x(t) + B_i u(t) \end{aligned} \quad (1)$$

where z_h , $h \in \mathcal{I}_p$ is the premise variable; $x \in \mathbb{R}^n$ and $u \in \mathbb{R}^m$ are the state and control input, respectively; Γ_{ih} , $(i, h) \in \mathcal{I}_r \times$

$\mathcal{I}_p$, is a fuzzy set for $z_h(t)$; A_i and B_i denote nominal system matrices with appropriate dimensions for the i th rule.

Using the center-average defuzzification, product inference, and singleton fuzzifier, the global dynamics is inferred as

$$\dot{x}(t) = \sum_{i=1}^r \mu_i(z(t)) (A_i x(t) + B_i u(t)) \quad (2)$$

where

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

$$\omega_i(z(t)) = \prod_{h=1}^p \Gamma_{ih}(z_h(t))$$

in which $\Gamma_{ih}(z_h(t))$ is the fuzzy membership grade of $z_h(t)$ in Γ_{ih} .

Suppose the pre-designed analog and the digital fuzzy controller (2).

$$u_c(t) = \sum_{i=1}^r \mu_i(z(t)) K_i^c x_c(t) \quad (3)$$

$$u_d(t) = u_d(kT) = \alpha(kT) \sum_{i=1}^r \mu_i(z(t)) K_i^d x_d(kT) \quad (4)$$

where K_i^c and K_i^d denote the analog and the digital control gains, the subscript 'c' and 'd' mean the analog control and the digital control, respectively, and $\alpha(kT)$ is a Bernoulli random process to determine the packet loss with the following assumption:

Assumption 1: Bernoulli random process $\alpha(kT)$ is an independent, identically distributed (iid) random sequence specified by the following law:

$$\begin{cases} \mathbf{Prob}\{\alpha(kT) = 1\} = \mathbb{E}\{\alpha(kT)\} = \tilde{\alpha} \\ \mathbf{Prob}\{\alpha(kT) = 0\} = 1 - \mathbb{E}\{\alpha(kT)\} = 1 - \tilde{\alpha} \end{cases}$$

Substituting (3) and (4) into (2), respectively, the closed-loop systems are written as

$$\dot{x}_c(t) = \sum_{i=1}^r \sum_{j=1}^r \mu_i(z(t)) \mu_j(z(t)) (A_i + B_i K_j^c) x_c(t) \quad (5)$$

$$\begin{aligned} \dot{x}_d(t) &= \sum_{i=1}^r \sum_{j=1}^r \mu_i(z(t)) \mu_j(z(kT)) \\ &\quad \times (A_i x(t) + \alpha(kT) B_i K_j^d x(kT)) \end{aligned} \quad (6)$$

To obtain the discretized systems of (5) and (6), we have introduced the following assumption.

Assumption 2: Assume that $\mu_i(z(t)) \approx \mu_i(z(kT))$ for $t \in [kT, kT + T)$. Consequently, the nonlinear matrix functions $\sum_{i=1}^r \mu_i(z(t)) A_i$ and $\sum_{i=1}^r \mu_i(z(t)) B_i$ can be represented by constant matrices $\sum_{i=1}^r \mu_i(z(kT)) A_i$ and $\sum_{i=1}^r \mu_i(z(kT)) B_i$, respectively, over any interval $[kT, kT + T)$, $k \in \mathbb{Z}_{\geq 0}$.

Supposing the sampling period T , closed-loop fuzzy system (5) and (6) are approximately discretized as

$$x_c(kT + T) \approx \sum_{i=1}^r \sum_{j=1}^r \mu_i(z(kT)) \mu_j(z(kT)) \Phi_{ij} x_c(kT) \quad (7)$$

where

$$\Phi_{ij} = \exp \left((A_i + B_i K_j^c) T \right)$$

$$\begin{aligned} x_d(kT + T) &\approx \sum_{i=1}^r \sum_{j=1}^r \mu_i(z(kT)) \mu_j(z(kT)) \\ &\quad \times \left((G_i + \alpha(kT) H_i K_j^d) T \right) x_d(kT) \end{aligned} \quad (8)$$

where

$$\begin{aligned} G_i &= \exp(A_i T), \\ H_i &= (G_i - I)(A_i)^{-1} B_i. \end{aligned}$$

The objective of this paper is to obtain the LMI for the digital fuzzy control gain K_i^d which minimize the state-matching error between $x_c(kT)$ and $x_d(kT)$ and stabilize the digital closed-loop system (6).

III. MAIN RESULTS

In order to proceed to main results, the following definition and lemmas will be needed throughout the proof.

Definition 1: The equilibrium point $x(t) = 0$ is said to be stochastically stable in the nonlinear system if, for any $\epsilon > 0$ there exists a $\delta = \delta(\epsilon) > 0$, such that

$$\|x(0)\| < \delta \Rightarrow E\{\|x(t)\|\} < \epsilon, \quad \forall t \geq 0$$

Lemma 1 ([14]): If there exist a Lyapunov functional and a non-decreasing convex function $a(r)$ satisfying the following conditions:

$$\begin{cases} V(0) = 0 \\ a(\|x(t)\|) \leq V(x(t)) \\ E\{V(x(t+1))\} - E\{V(x(t))\} < 0 \end{cases}$$

then the equilibrium point $x(t) = 0$ of the fuzzy system (8) is stochastically stable.

Lemma 2 ([15]): Given any matrices Y and $P = P^T \succ 0$, we have

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

Lemma 3 ([16]): : For any real matrices X_i, Y_i for $1 \leq i \leq N$, and $S \succ 0$ with appropriate dimensions, we have

$$\begin{aligned} &2 \sum_{i=1}^N \sum_{j=1}^N \sum_{k=1}^N \sum_{l=1}^N h_i h_j h_k h_l X_{ij}^T S Y_{kl} \\ &\leq \sum_{i=1}^N \sum_{j=1}^N h_i h_j (X_{ij}^T S X_{ij} + Y_{ij}^T S Y_{ij}) \end{aligned}$$

where h_i ($1 \leq i \leq N$) are defined as $h_i \geq 0$, $\sum_{i=1}^N h_i = 1$.

Lemma 4 ([17]): : For real matrices X and Y with appropriate dimensions, the following inequality is always satisfied.

$$X^T Y + Y^T X \leq \sigma X^T X + \frac{1}{\sigma} Y^T Y$$

where σ is a positive constant.

Proposition 1: In (6), there exists some constant $\delta > 0$ such that

$$\mathbb{E}\{\|x(t)\|\} \leq \delta \mathbb{E}\{\|x(kT)\|\} \quad (9)$$

where

$$\begin{aligned} \delta &= (1 + T\beta)e^{\alpha T}, \\ \alpha &= \sup_{i \in \mathcal{I}_r} \|A_i\|, \\ \beta &= \sup_{(i,j) \in \mathcal{I}_r \times \mathcal{I}_r} \|B_i K_j^d\| \end{aligned}$$

for $t \in [kT, kT + T)$.

Proof: Integrating (6) from kT to t , $t \in [kT, kT + T)$ and taking the norm on both sides of the results yields

$$\begin{aligned} \|x(t)\| &\leq \|x(kT)\| + \int_{kT}^t \left(\left\| \sum_{i=1}^r \mu_i(z(t)) A_i \right\| \|x(\tau)\| \right. \\ &\quad \left. + \left\| \sum_{i=1}^r \sum_{j=1}^r \mu_i(z(t)) \mu_j(z(kT)) \alpha(kT) B_i K_j \right\| \|x(kT)\| \right) d\tau \\ &\leq \sup_{(i,j) \in \mathcal{I}_r \times \mathcal{I}_r} \left\{ (1 + T\|B_i K_j^d\|) \|x(kT)\| + \int_{kT}^t \|A_i\| \|x(\tau)\| d\tau \right\} \end{aligned}$$

An application of the Grownwall-Bellman inequality to $\|x(t)\|$ constructs the inequality

$$\|x(t)\| \leq \delta \|x(kT)\| \quad (10)$$

where

$$\delta = \sup_{(i,j) \in \mathcal{I}_r \times \mathcal{I}_r} \left\{ (1 + T\|B_i K_j^d\|) e^{\|A_i\|T} \right\}$$

is independent of k . Taking the expectation of (10), we can obtain the inequality (1). ■

Theorem 1: If there exist some symmetric and positive matrix Q and some matrix M_i , such that the following LMIs have optimal solutions, then, $x_d(kT)$ of (8) closely matches $x_c(kT)$ of (7), and origin of (8) is stochastically stable.

minimize γ subject to

$$\begin{bmatrix} -\gamma Q & * & * \\ \Phi_{ij}Q - G_iQ - \tilde{\alpha}H_iM_j & -\gamma I & * \\ \sqrt{(1-\tilde{\alpha})\tilde{\alpha}}H_iM_j & 0 & -\gamma I \end{bmatrix} \prec 0 \quad (11)$$

$$\begin{bmatrix} -Q & * & * \\ G_iQ + \tilde{\alpha}H_iM_i & -Q & * \\ \sqrt{(1-\tilde{\alpha})\tilde{\alpha}}H_iM_j & 0 & -Q \end{bmatrix} \prec 0 \quad (12)$$

$$\begin{bmatrix} -4Q & * & * \\ G_iQ + G_jQ + \tilde{\alpha}H_iM_j + \tilde{\alpha}H_jM_i & -Q & * \\ \sqrt{(1-\tilde{\alpha})\tilde{\alpha}}(H_iM_j + H_jM_i) & 0 & -Q \end{bmatrix} \prec 0 \quad (13)$$

for $\forall \{(i,j) \in \mathcal{I}_r \times \mathcal{I}_r | 1 \leq i \leq j \leq r\}$.

Proof: In order to closely match $x_d(kT)$ of (8) to $x_c(kT)$ of (7), consider the norm minimization problem in the following form:

$$\left\| \Phi_{ij}^k - (G_i + \alpha(kT)H_iK_j^d) \right\| \leq \hat{\gamma} \quad (14)$$

for some $\hat{\gamma} > 0$. Using the norm property, the above inequality holds

$$\begin{aligned} &\left(\Phi_{ij} - (G_i + \alpha(kT)H_iK_j^d) \right)^T \left(\Phi_{ij} - (G_i + \alpha(kT)H_iK_j^d) \right) \\ &\prec \gamma^2 P \end{aligned} \quad (15)$$

where $\gamma > 0$ and $P^k = (P)^T \succ 0$ with $\hat{\gamma}I \prec \gamma^2 P$. Taking the expectation, inequality (15) results in

$$\begin{aligned} (15) \Rightarrow E \left\{ \left(\Phi_{ij} - (\Psi_{ij} + \hat{\alpha}(kT)H_iK_j^d) \right)^T \right. \\ \left. \times \left(\Phi_{ij} - (\Psi_{ij} + \hat{\alpha}(kT)H_iK_j^d) \right) - \gamma^2 P \right\} \\ = (\Phi_{ij} - \Psi_{ij})^T (\Phi_{ij} - \Psi_{ij}) - \gamma^2 P \\ + (1 - \tilde{\alpha})\tilde{\alpha}(K_j^d)^T H_i^T H_i K_j^d \end{aligned} \quad (16)$$

where

$$\begin{aligned} \Psi_{ij} &= G_i + \tilde{\alpha}H_iK_j^d, \\ \hat{\alpha}(kT) &= \alpha(kT) - \tilde{\alpha}. \end{aligned}$$

Taking the Schur complement and the congruence transformation with $\text{diag}\{\gamma^{-1}P^{-1}, I, I\}$ and denoting $K_j^d Q = M_j$, inequality (15) yields (11).

Apart from the state-matching problem, for solving the stability problem, we choose the Lyapunov function candidate $V(x(kT))$ for (8) as follows:

$$V(x(kT)) = x_d^T(kT) P x_d(kT)$$

The rate of increase of $E\{V(x(kT))\}$ along (8) is then

$$\begin{aligned} E\{V(kT+T)\} - E\{V(kT)\} &\leq E \left\{ \frac{1}{4} \sum_{i=1}^r \sum_{j=1}^r \mu_i(z(kT)) \mu_j(z(kT)) \right. \\ &\quad \times \left(\left((\Psi_{ij} + \Psi_{ji} + \hat{\alpha}(kT)H_iK_j^d + \hat{\alpha}(kT)H_jK_i^d)x_d \right)^T \right. \\ &\quad \times P^k \left((\Psi_{ij} + \Psi_{ji} + \hat{\alpha}(kT)H_iK_j^d + \hat{\alpha}(kT)H_jK_i^d)x_d \right) \\ &\quad \left. \left. - 4x_d^T P^k x_d \right) \right\} \end{aligned} \quad (17)$$

Because of $\mathbb{E}\{\hat{\alpha}(kT)\} = 0$ and $\mathbb{E}\{\hat{\alpha}^2(kT)\} = (1 - \tilde{\alpha})\tilde{\alpha}$, inequality (17) is rearranged as follows:

$$\begin{aligned} E\{V(kT+T)\} - E\{V(kT)\} &\leq \frac{1}{4} \sum_{i=1}^r \sum_{j=1}^r \mu_i(z(kT)) \mu_j(z(kT)) \\ &\quad \times \left(\left((\Psi_{ij} + \Psi_{ji})x_d \right)^T P \left((\Psi_{ij} + \Psi_{ji})x_d \right) - 4x_d^T P^k x_d \right. \\ &\quad \left. + (1 - \tilde{\alpha})\tilde{\alpha}x_d^T (H_iK_j^d + H_jK_i^d)^T P (H_iK_j^d + H_jK_i^d)x_d \right) \end{aligned} \quad (18)$$

Form (18), if the following inequalities hold for any $1 \leq i < j \leq r$, we know that the closed-loop system (6) is

stochastically stable by Definition 1 and Proposition 1.

$$\Psi_{ii}^T P \Psi_{ii} - P + (1 - \tilde{\alpha}) \alpha (K_j^d)^T H_i^T P H_i K_j^d \prec 0 \quad (19)$$

$$\begin{aligned} & \left(\frac{\Psi_{ij} + \Psi_{ji}}{2} \right)^T P \left(\frac{\Psi_{ij} + \Psi_{ji}}{2} \right) - P \\ & + (1 - \tilde{\alpha}) \alpha \left(\frac{H_i K_j^d + H_j K_i^d}{2} \right)^T P \left(\frac{H_i K_j^d + H_j K_i^d}{2} \right) \prec 0 \end{aligned} \quad (20)$$

Using Schur complement and congruence transformation with $\text{diag}\{P^{-1}, I, I\}$ to (19) and (20), we can obtain the LMI conditions (12) and (13) in the Theorem 1. ■

Remark 1: The inequalities for the pair (k, m) such that $\mu_{ik}(x_i(t)) \times \mu_{im}(x_i(t)) = 0$, do not need to be solved to determine global stability.

IV. NUMERICAL EXAMPLES

In this section, an example is given to validate the proposed method. We consider the fuzzy system which is called the chaotic Lorenz system. The dynamic equations of the system are described by [18]

$$\begin{aligned} \dot{w}(t) &= -\sigma w(t) + \sigma y(t) \\ \dot{y}(t) &= r w(t) - y(t) - w(t)z(t) \\ \dot{z}(t) &= w(t)y(t) - b z(t) \end{aligned}$$

where $\sigma = 10$, $r = 28$ and $b = -\frac{8}{3}$.

Assuming $w(t) \in [M_1, M_2]$ and choosing $x(t) = [x_1(t) \ x_2(t) \ x_3(t)]^T = [w(t) \ y(t) \ z(t)]^T$, the T-S fuzzy system can be constructed as follows:

$$\dot{x}(t) = \sum_{i=1}^2 \mu_i(x_1(t)) (A_i x(t) + B_i u(t))$$

where

$$\begin{aligned} A_1 &= \begin{bmatrix} -\sigma & \sigma & 0 \\ r & -1 & -M_1 \\ 0 & M_1 & -b \end{bmatrix} \\ A_2 &= \begin{bmatrix} -\sigma & \sigma & 0 \\ r & -1 & -M_2 \\ 0 & M_2 & -b \end{bmatrix} \\ B_1 &= B_2 = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \end{aligned}$$

for $i \in \mathcal{I}_r$. The membership functions are

$$\begin{aligned} \mu_1(x_1(t)) &= \frac{-x_1(t) + M_2}{M_2 - M_1} \\ \mu_2(x_1(t)) &= \frac{x_1(t) - M_1}{M_2 - M_1} \end{aligned}$$

We assume $M_1 = -20$, $M_2 = 30$, the initial sate conditions $x(0) = [10, -10, -10]^T$, packet loss probability $\tilde{\alpha} = 0.8$ and a sampling time $T = 0.05s$.

By using Theorem 1 and solving the corresponding LMIs, we obtain the control gains:

$$\begin{aligned} K_1^d &= [-25.0411 \quad -15.8009 \quad -11.6152] \\ K_2^d &= [-23.4177 \quad -10.0505 \quad 15.5128] \end{aligned}$$

Time responses for each subsystem are shown in Figs. 1, 2 and 3. As shown in these figures, we can observe that the controlled state variables by IDR method follow the controlled analog ones and converge to the origin. Thus we can know that the proposed IDR technique satisfies an asymptotic stability of digitally closed-loop fuzzy system and the state-matching requirement with the originally closed-loop system.

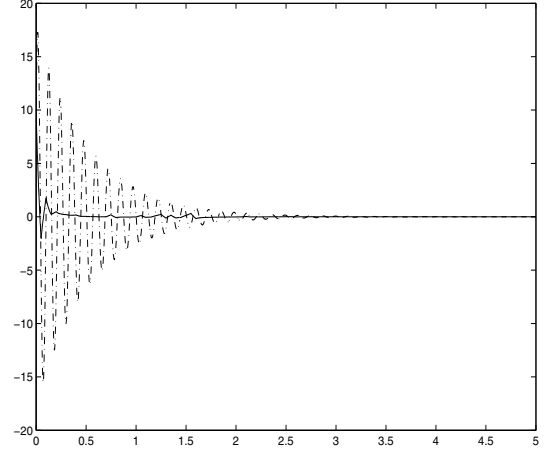


Fig. 1. The time responses x_1 of controlled system for $T = 0.2s$: analog (dash-dotted), proposed (solid).

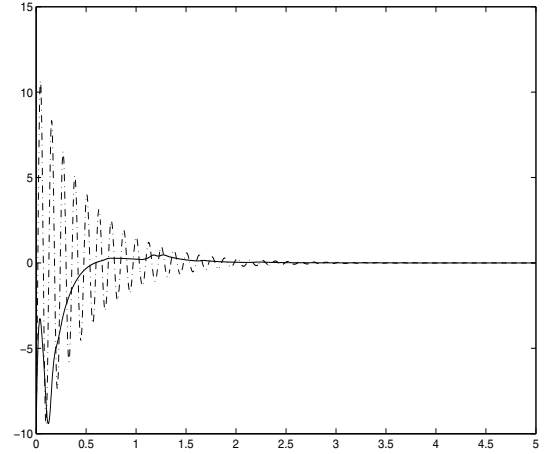


Fig. 2. The time responses x_2 of controlled system for $T = 0.2s$: analog (dash-dotted), proposed (solid).

V. CONCLUSION

This paper has established the IDR method for the fuzzy systems. Using the T-S fuzzy model, we has presented the analog and digital closed-loop fuzzy systems. For the IDR method, descritized models of each closed-loop systems are obtained. Based on the descritized systems, it was shown that the IDR technique can find the digital fuzzy gains to minimize the norm error between the state of analog system and digital system and stabilize the digital closed-loop system. Also, the sufficient design conditions were derived and formulated in the LMI format, and were therefore easily tractable by convex

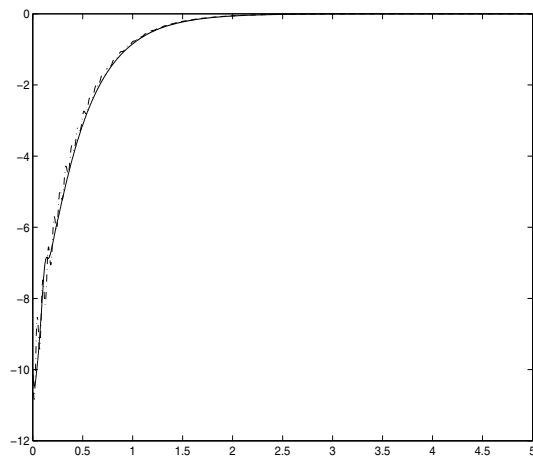


Fig. 3. The time responses x_3 of controlled system for $T = 0.2s$: analog (dash-dotted), proposed (solid).

optimization. Finally a simulation example has shown that the results of this paper are effective and valuable.

ACKNOWLEDGMENT

This research was supported by Basic Research Program through the National Research Foundation of Korea(NRF) funded by the Ministry of Education, Science and Technology(2010-0024352).

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