Stability Analysis and Design of Fuzzy Observer-Controller for Fuzzy Systems¹

H.K. Lam, F.H.F. Leung and P.K.S. Tam

Centre for Multimedia Signal Processing, Department of Electronic and Information Engineering, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong

Abstract

Stability of a fuzzy system controlled by a fuzzy observer-controller will be investigated in this paper. In general, the stability condition is a common solution of [p(p+1)+2p)]/2 linear matrix inequalities (LMIs) where p is the number of rules of the fuzzy plant model. In this paper, the number is reduced to 2p+1. Furthermore, gains of the fuzzy observer-controller can be derived from the solution of the LMIs. Separation principle of the fuzzy observer-controller will be proved.

I. INTRODUCTION

Nonlinear system can be represented by a TSK fuzzy model [1-2]. It expresses the dynamics of the nonlinear plant as a weighted sum of some linear systems. This model can be obtained by using system identification methods [1-2, 7, 14] or direct derivation from the mathematical model. Sufficient stability conditions have been derived for the control systems comprising the fuzzy plant model and a fuzzy controller [5-6, 8-10, 13]. In order to deal with plants with immeasurable system states, fuzzy observer-controllers were proposed [3, 12]. In [3, 12], sufficient stability conditions were derived: there

exists a common positive definite solution $P \in \Re^{2n \times 2n}$ in

$$\frac{p(p+1)}{2}$$
 linear matrix inequalities (LMIs) [3], where n and p

are numbers of system states and fuzzy rules of the fuzzy plant model respectively. Based on the analysis results in [3,12] and

positive definite matrices, the separation principle can be applied [12]. The fuzzy observer-controller control system is guaranteed to be stable if there are common positive definite p(p+1) = p(p+1)

solutions
$$\mathbf{P}_p \in \mathfrak{R}^{n \times n}$$
 in $\frac{p(p+1)}{2}$ LMIs and $\mathbf{P}_e \in \mathfrak{R}^{n \times n}$ in p

LMIs. If the input matrix is linear, a linear closed-loop system can be obtained under some conditions [4]. The contributions of this paper are threefold. First, a fuzzy observer-controller is proposed such that the total number of the LMIs of the stability

conditions is reduced to 2p+1. The chance of finding the

solution will thus be increased. Second, a methodology is derived to design the gains of the fuzzy observer-controller. Third, the separation principle will still hold.

II. FUZZY PLANT MODEL, CONTROLLER AND OBSERVER

The nonlinear plant to be tackled is of the following form,
$$\begin{cases} \dot{\mathbf{x}}(t) = \mathbf{A}(\mathbf{x}(t))\mathbf{x}(t) + \mathbf{B}(\mathbf{x}(t))\mathbf{u}(t) \\ \mathbf{y}(t) = \mathbf{C}(\mathbf{x}(t))\mathbf{x}(t) \end{cases}$$
(1)

where $\mathbf{A}(\mathbf{x}(t)) \in \mathfrak{R}^{n \times n}$ and $\mathbf{B}(\mathbf{x}(t)) \in \mathfrak{R}^{n \times m}$ are known system and input matrices respectively, $\mathbf{x}(t) \in \mathfrak{R}^{n \times 1}$ is the fully or partially immeasurable system state vector and $\mathbf{u}(t) \in \mathfrak{R}^{m \times 1}$ is the input vector; $\mathbf{y}(t) \in \mathfrak{R}^{l \times 1}$ is the system output vector and $\mathbf{C}(\mathbf{x}(t)) \in \mathfrak{R}^{l \times n}$ is the output matrix. The system of (1) is represented by a fuzzy plant model, which expresses the nonlinear plant as a weighted sum of linear systems. A fuzzy observer-controller is used to close the feedback loop.

A. Fuzzy Plant Model

 $\mathbf{y}(t) = \mathbf{C}_i \mathbf{x}(t)$

Let p be the number of fuzzy rules,

Rule *i*: IF
$$f_1$$
 is M_1^i and ... and f_{Ψ} is M_{Ψ}^i THEN
$$\begin{cases} \dot{\mathbf{x}}(t) = \mathbf{A}_1 \mathbf{x}(t) + \mathbf{B}_i \mathbf{u}(t) \end{cases}$$
(2)

where \mathbf{M}_{α}^{i} is a fuzzy term of rule i corresponding to f_{α} which is a function of the measurable system states or output states of the nonlinear plant, $\alpha=1,\ldots, \mathcal{Y}, i=1,\ldots, p$, \mathcal{Y} is a positive integer; $\mathbf{A}_{i}\in\mathfrak{R}^{n\times n}$, $\mathbf{B}_{i}\in\mathfrak{R}^{n\times m}$ and $\mathbf{C}_{i}\in\mathfrak{R}^{l\times n}$ are the known system, input and output matrices of the i-th rule sub-system respectively. The system dynamics are described by,

$$\begin{cases} \dot{\mathbf{x}}(t) = \sum_{i=1}^{p} w_i (\mathbf{A}_i \mathbf{x}(t) + \mathbf{B}_i \mathbf{u}(t)) \\ \mathbf{y}(t) = \sum_{i=1}^{p} w_i \mathbf{C}_i \mathbf{x}(t) \end{cases}$$
(3)

where
$$\sum_{i=1}^{p} w_i = 1$$
, $w_i \in [0 \ 1]$ for all i (4)

$$w_{i} = \frac{\mu_{M_{1}^{i}}(f_{1}) \times \mu_{M_{2}^{i}}(f_{2}) \times \dots \times \mu_{M_{\Psi}^{i}}(f_{\Psi})}{\sum_{k=1}^{p} \left(\mu_{M_{1}^{k}}(f_{1}) \times \mu_{M_{2}^{k}}(f_{2}) \times \dots \times \mu_{M_{\Psi}^{k}}(f_{\Psi})\right)}$$
(5)

is a nonlinear function of the measurable system states or output states, $\mu_{\rm ML}(f_k)$ is the grade of membership of the

fuzzy term M_k^i . (Fuzzy modeling is discussed in [1-2, 7, 14].)

B. Fuzzy Observer

A fuzzy observer having p fuzzy rules is to be designed. The j-th rule of the fuzzy observer is of the following format: Rule j: IF f_1 is M_j^j and ... and f_{Ψ} is M_{Ψ}^j

THEN
$$\hat{\mathbf{x}}(t) = \mathbf{A}_i \hat{\mathbf{x}}(t) + \mathbf{B}_i \mathbf{u}(t) + \mathbf{K}_i \mathbf{C}_i \mathbf{e}(t)$$
 (6)

where $\hat{\mathbf{x}}(t) \in \Re^{n \times l}$ is the estimate of the system state $\mathbf{x}(t)$,

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 $\mathbf{K}_{j} \in \Re^{n \times l}$, j = 1, 2, ..., p, are the observer gains to be designed, $\mathbf{e}(t) = \mathbf{x}(t) - \hat{\mathbf{x}}(t)$. The fuzzy observer has the same antecedents of the fuzzy plant model of (2). The dynamics of the fuzzy observer are described by,

$$\dot{\hat{\mathbf{x}}}(t) = \sum_{i=1}^{p} w_{j} \left(\mathbf{A}_{j} \hat{\mathbf{x}}(t) + \mathbf{B}_{j} \mathbf{u}(t) + \mathbf{K}_{j} \mathbf{C}_{j} \mathbf{e}(t) \right)$$
(7)

It should be noted that although the sub-observer in each rule is a full-state observer, it can be a partial-state observer as w_j can be a function of the known states in addition to y(t).

C. Fuzzy Controller

A fuzzy controller having p fuzzy rules is to be designed for the plant. The k-th rule is of the following format:

Rule k: IF f_1 is M_1^k and ... and f_{ψ} is M_{ψ}^k

THEN
$$\mathbf{u}(t) = m_k(\hat{\mathbf{x}}(t))\mathbf{G}_k\hat{\mathbf{x}}(t)$$
 (8)

where $G_k \in \mathbb{R}^{m \times n}$ is the feedback gain of rule k, k = 1, 2, ..., p; $m_k(\hat{\mathbf{x}}(t))$ is a scalar gain depending on the estimated states and has the following property,

$$\sum_{k=1}^{p} w_k m_k(\hat{\mathbf{x}}(t)) = 1 \tag{9}$$

Both G_k and $m_k(\hat{\mathbf{x}}(t))$ are to be designed. Then, the inferred output of the fuzzy controller is given by,

$$\mathbf{u}(t) = \sum_{k=1}^{P} w_k m_k(\hat{\mathbf{x}}(t)) \mathbf{G}_k \hat{\mathbf{x}}(t)$$
 (10)

III. STABILITY ANALYSIS AND GAIN DESIGN

In the following, we shall analyze the stability and robustness of the fuzzy observer-controller control system and give the design of $m_k(\hat{\mathbf{x}}(t))$. From (3) and (10), writing $m_k(\hat{\mathbf{x}}(t))$ as m_k and making use of the properties of (4) and

(9),
$$\sum_{i=1}^{p} w_i = \sum_{j=1}^{p} w_j m_j = 1$$
, the closed-loop system is given by,

$$\dot{\mathbf{x}}(t) = \sum_{i=1}^{p} w_i \left(\mathbf{A}_i \mathbf{x}(t) + \mathbf{B}_i \sum_{k=1}^{p} w_k m_k \mathbf{G}_k \hat{\mathbf{x}}(t) \right)$$

$$=\mathbf{H}\hat{\mathbf{x}}(t) + \sum_{i=1}^{p} \sum_{k=1}^{p} w_{i} w_{k} m_{k} \mathbf{H}_{ik} \hat{\mathbf{x}}(t) + \sum_{i=1}^{p} w_{i} \mathbf{A}_{i} \mathbf{e}(t)$$
(11)

where $\mathbf{H}_{ik} = \mathbf{A}_i + \mathbf{B}_i \mathbf{G}_k - \mathbf{H}$

 $\mathbf{H} \in \mathbb{R}^{n \times n}$ is a stable matrix to be designed. To study the stability of (11), consider the following Lyapunov function.

$$V_{p}(\mathbf{x}(t)) = \frac{1}{2}\mathbf{x}(t)^{\mathsf{T}}\mathbf{P}_{p}\mathbf{x}(t)$$
 (13)

where $P_n \in \Re^{n \times n}$ is a symmetric positive definite matrix.

$$\dot{V}_{p}(\mathbf{x}(t)) = \frac{1}{2} \left(\dot{\mathbf{x}}(t)^{\mathsf{T}} \mathbf{P}_{p} \mathbf{x}(t) + \mathbf{x}(t)^{\mathsf{T}} \mathbf{P}_{p} \dot{\mathbf{x}}(t) \right)$$
(14)

From (11) and (14), we have,

$$\begin{split} \dot{V}_{p}\left(\mathbf{x}(t)\right) &= \frac{1}{2} \left(\mathbf{H}\hat{\mathbf{x}}(t) + \sum_{i=1}^{p} \sum_{k=1}^{p} w_{i} w_{k} m_{k} \mathbf{H}_{ik} \hat{\mathbf{x}}(t) + \sum_{i=1}^{p} w_{i} \mathbf{A}_{i} \mathbf{e}(t)\right)^{T} \mathbf{P}_{p} \mathbf{x}(t) \\ &+ \frac{1}{2} \mathbf{x}(t)^{T} \mathbf{P}_{p} \left(\mathbf{H}\hat{\mathbf{x}}(t) + \sum_{i=1}^{p} \sum_{k=1}^{p} w_{i} w_{k} m_{k} \mathbf{H}_{ik} \hat{\mathbf{x}}(t) + \sum_{i=1}^{p} w_{i} \mathbf{A}_{i} \mathbf{e}(t)\right) \end{split}$$

$$= \frac{1}{2}\hat{\mathbf{x}}(t)^{\mathsf{T}}\mathbf{H}^{\mathsf{T}}\mathbf{P}_{p}\mathbf{x}(t) + \frac{1}{2}\mathbf{x}(t)^{\mathsf{T}}\mathbf{P}_{p}\mathbf{H}\hat{\mathbf{x}}(t) + \frac{1}{2}\sum_{i=1}^{p}\sum_{k=1}^{p}w_{i}w_{k}m_{k}\hat{\mathbf{x}}(t)^{\mathsf{T}}\mathbf{H}_{ik}{}^{\mathsf{T}}\mathbf{P}_{p}\mathbf{x}(t) + (15)$$

$$+ \frac{1}{2}\sum_{i=1}^{p}\sum_{k=1}^{p}w_{i}w_{k}m_{k}\mathbf{x}(t)^{\mathsf{T}}\mathbf{P}_{p}\mathbf{H}_{a}\hat{\mathbf{x}}(t) + \sum_{i=1}^{p}w_{i}\mathbf{x}(t)^{\mathsf{T}}\mathbf{P}_{p}\mathbf{A}_{i}\mathbf{e}(t)$$
From (15) and $\mathbf{e}(t) = \mathbf{x}(t) - \hat{\mathbf{x}}(t)$, we have,
$$\hat{V}_{p}(\mathbf{x}(t)) = \frac{1}{2}(\mathbf{x}(t) - \mathbf{e}(t))^{\mathsf{T}}\mathbf{H}^{\mathsf{T}}\mathbf{P}_{p}\mathbf{x}(t) + \frac{1}{2}\mathbf{x}(t)^{\mathsf{T}}\mathbf{P}_{p}\mathbf{H}(\mathbf{x}(t) - \mathbf{e}(t))$$

$$+ \frac{1}{2}\sum_{i=1}^{p}\sum_{k=1}^{p}w_{i}w_{k}m_{k}\hat{\mathbf{x}}(t)^{\mathsf{T}}\mathbf{H}_{ik}^{\mathsf{T}}\mathbf{P}_{p}(\mathbf{e}(t) + \hat{\mathbf{x}}(t)) +$$

$$+ \frac{1}{2}\sum_{i=1}^{p}\sum_{k=1}^{p}w_{i}w_{k}m_{k}(\mathbf{e}(t) + \hat{\mathbf{x}}(t))^{\mathsf{T}}\mathbf{P}_{p}\mathbf{H}_{ik}\hat{\mathbf{x}}(t) + \sum_{i=1}^{p}w_{i}\mathbf{x}(t)^{\mathsf{T}}\mathbf{P}_{p}\mathbf{A}_{i}\mathbf{e}(t)$$

$$= -\frac{1}{2}\mathbf{x}(t)^{\mathsf{T}}\mathbf{Q}_{p}\mathbf{x}(t) - \mathbf{x}(t)^{\mathsf{T}}\mathbf{P}_{p}\mathbf{H}\mathbf{e}(t) - \frac{1}{2}\sum_{i=1}^{p}\sum_{k=1}^{p}w_{i}w_{k}m_{k}\hat{\mathbf{x}}(t)^{\mathsf{T}}\mathbf{Q}_{ik}\hat{\mathbf{x}}(t)$$
(16)

$$= -\frac{1}{2}\mathbf{x}(t)^{\mathsf{T}}\mathbf{Q}_{p}\mathbf{x}(t) - \mathbf{x}(t)^{\mathsf{T}}\mathbf{P}_{p}\mathbf{H}\mathbf{e}(t) - \frac{1}{2}\sum_{i=1}^{p}\sum_{k=1}^{m}w_{i}w_{k}m_{k}\hat{\mathbf{x}}(t)^{\mathsf{T}}\mathbf{Q}_{ik}\hat{\mathbf{x}}(t)$$

$$+\sum_{i=1}^{p}\sum_{k=1}^{p}w_{i}w_{k}m_{k}\mathbf{e}(t)^{\mathsf{T}}\mathbf{P}_{p}\mathbf{H}_{ik}(\mathbf{x}(t) - \mathbf{e}(t)) + \sum_{i=1}^{p}w_{i}\mathbf{x}(t)^{\mathsf{T}}\mathbf{P}_{p}\mathbf{A}_{i}\mathbf{e}(t)$$
(16)

where $\mathbf{Q}_p \in \Re^{n \times n}$ and $\mathbf{Q}_{ij} \in \Re^{n \times n}$, i = 1, 2, ..., p; k = 1, 2, ..., p, are symmetric positive definite matrix and symmetric matrices respectively. They are defined as follows,

$$\mathbf{Q}_{p} = -\left(\mathbf{H}^{\mathsf{T}}\mathbf{P}_{p} + \mathbf{P}_{p}\mathbf{H}\right) \tag{17}$$

$$\mathbf{Q}_{ik} = -\left(\mathbf{H}_{ik}^{\mathsf{T}} \mathbf{P}_{p} + \mathbf{P}_{p} \mathbf{H}_{ik}\right), i = 1, 2, ..., p; k = 1, 2, ..., p$$
 (18)

Based on the Rayleigh principle, the following property holds for a symmetric positive definite matrix $P \in \mathbb{R}^{n \times n}$,

$$0 < \lambda_{\min}(\mathbf{P}) \|\mathbf{x}(t)\|^2 \le \mathbf{x}(t)^{\mathrm{T}} \mathbf{P} \mathbf{x}(t) \le \lambda_{\max}(\mathbf{P}) \|\mathbf{x}(t)\|^2$$
 (19) where $\lambda_{\max}(\mathbf{P})$ and $\lambda_{\min}(\mathbf{P})$ are the maximum and minimum eigenvalues of \mathbf{P} respectively, $\|\cdot\|$ denotes the l_2 norm for vectors and l_2 induced norm for matrices. Then, (16) implies,

$$V_{p}(\mathbf{x}(t)) \leq -\frac{1}{2} \lambda_{\min} (\mathbf{Q}_{p}) \|\mathbf{x}(t)\|^{2} - \frac{1}{2} \sum_{i=1}^{p} \sum_{k=1}^{p} w_{i} w_{k} m_{k} \hat{\mathbf{x}}(t)^{\mathsf{T}} \mathbf{Q}_{ik} \hat{\mathbf{x}}(t)$$

$$+ \|\mathbf{P}_{p} \mathbf{H} \| \|\mathbf{x}(t) \| \|\mathbf{e}(t) \| + \sum_{i=1}^{p} \sum_{k=1}^{p} w_{i} w_{k} m_{k} \|\mathbf{P}_{p} \mathbf{H}_{ik} \| \|\mathbf{x}(t) \| \|\mathbf{e}(t) \|$$

$$+ \sum_{i=1}^{p} \sum_{k=1}^{p} w_{i} w_{k} m_{k} \|\mathbf{P}_{p} \mathbf{H}_{ik} \| \|\mathbf{e}(t) \|^{2} + \sum_{i=1}^{p} w_{i} \|\mathbf{P}_{p} \mathbf{A}_{i} \| \|\mathbf{x}(t) \| \|\mathbf{e}(t) \|$$

$$(20)$$

From (20), (4) and (9),
$$\sum_{i=1}^{p} w_i = \sum_{j=1}^{p} w_j m_j = 1$$
, (20) becomes,

$$\begin{split} \dot{\mathcal{V}}_{p}(\mathbf{x}(t)) &\leq -\frac{1}{2} \lambda_{\min}(\mathbf{Q}_{p}) \left\| \mathbf{x}(t) \right\|^{2} - \frac{1}{2} \sum_{t=1}^{p} \sum_{k=1}^{p} w_{t} w_{k} m_{k} \hat{\mathbf{x}}(t)^{\mathsf{T}} \mathbf{Q}_{:k} \hat{\mathbf{x}}(t) \\ &+ \left\| \mathbf{P}_{p} \mathbf{H}_{k} \right\|_{\max} + \left\| \mathbf{P}_{p} \mathbf{A}_{:k} \right\|_{\max} \left\| \mathbf{x}(t) \right\| \left\| \mathbf{e}(t) \right\| + \left\| \mathbf{P}_{p} \mathbf{H}_{:k} \right\|_{\max} \left\| \mathbf{e}(t) \right\|^{2} \end{split}$$

$$= -\frac{1}{2} \lambda_{\min} (\mathbf{Q}_{p}) \|\mathbf{x}(t)\|^{2} - \frac{1}{2} \sum_{i=1}^{p} \sum_{k=1}^{p} w_{i} w_{k} M_{k}^{(2)} \hat{\mathbf{x}}(t)^{\mathsf{T}} \mathbf{Q}_{ik} \hat{\mathbf{x}}(t) + \gamma \|\mathbf{x}(t)\| \|\mathbf{e}(t)\| + \|\mathbf{P}_{p}\mathbf{H}_{ik}\|_{\max} \|\mathbf{e}(t)\|^{2}$$
(21)

where
$$\|\mathbf{P}_{p}\mathbf{H}_{ik}\|_{\max} = \max_{i,k} \|\mathbf{P}_{p}\mathbf{H}_{ik}\| \ge 0$$
 (22)

$$\left\| \mathbf{P}_{p} \mathbf{A}_{i} \right\|_{\text{max}} = \max \left\| \mathbf{P}_{p} \mathbf{A}_{i} \right\| \ge 0 \tag{23}$$

(14)
$$\gamma = \|\mathbf{P}_{p}\mathbf{H}\| + \|\mathbf{P}_{p}\mathbf{H}_{ik}\|_{\max} + \|\mathbf{P}_{p}\mathbf{A}_{i}\|_{\max} \ge 0$$
 (24)

From (21)

$$\dot{V}_{p}(\mathbf{x}(t)) \leq -\frac{1}{4} \lambda_{\min}(\mathbf{Q}_{p}) \|\mathbf{x}(t)\|^{2} - \frac{1}{2} \sum_{k=1}^{p} w_{k} m_{k} \hat{\mathbf{x}}(t)^{\mathsf{T}} \sum_{i=1}^{p} w_{i} \mathbf{Q}_{ik} \hat{\mathbf{x}}(t)$$

$$-\frac{1}{4} \lambda_{\min}(\mathbf{Q}_{p}) \|\mathbf{x}(t)\|^{2} + \gamma \|\mathbf{x}(t)\| \|\mathbf{e}(t)\| + \|\mathbf{P}_{p}\mathbf{H}_{ik}\|_{\max} \|\mathbf{e}(t)\|^{2}$$
(25)

Consider the following inequality,

$$\left(\sqrt{\frac{1}{4} \lambda_{\min}(\mathbf{Q}_{p})} \|\mathbf{x}(t)\| - \frac{\gamma}{2\sqrt{\frac{1}{4} \lambda_{\min}(\mathbf{Q}_{p})}} \|\mathbf{e}(t)\| \right)^{2} \ge 0$$

$$\Rightarrow \frac{1}{4} \lambda_{\min}(\mathbf{Q}_{p}) \|\mathbf{x}(t)\|^{2} - \gamma \|\mathbf{x}(t)\| \|\mathbf{e}(t)\| + \frac{\gamma^{2}}{\lambda_{\min}(\mathbf{Q}_{p})} \|\mathbf{e}(t)\|^{2} \ge 0$$

$$\Rightarrow \frac{\gamma^{2}}{\lambda_{\min}(\mathbf{Q}_{p})} \|\mathbf{e}(t)\|^{2} \ge -\frac{1}{4} \lambda_{\min}(\mathbf{Q}_{p}) \|\mathbf{x}(t)\|^{2} + \gamma \|\mathbf{x}(t)\| \|\mathbf{e}(t)\| \quad (26)$$

$$\begin{aligned} \dot{V}_{p}(\mathbf{x}(t)) &\leq -\frac{1}{4} \lambda_{\min}(\mathbf{Q}_{p}) \|\mathbf{x}(t)\|^{2} \\ &-\frac{1}{2} \sum_{k=1}^{p} w_{k} m_{k} \hat{\mathbf{x}}(t)^{\mathsf{T}} \sum_{k=1}^{p} w_{i} \mathbf{Q}_{ik} \hat{\mathbf{x}}(t) + \left(\frac{Y^{2}}{\lambda_{\min}(\mathbf{Q}_{k})} + \|\mathbf{P}_{p}\mathbf{H}_{ik}\|_{\max}\right) \|\mathbf{e}(t)\|^{2} \end{aligned}$$
(27)

Let m_k , k = 1, 2, ..., p, be designed as follows,

$$m_{k} = \begin{cases} 1 & \text{if } w_{k} = 0 \\ \frac{n_{s}}{w_{k} \sum_{s=1}^{p} n_{s}} & \text{otherwise} \end{cases}$$

$$m_{k} = \begin{cases} \frac{1}{w_{k} \sum_{s=1}^{p} n_{s}} & \text{otherwise} \end{cases}$$

$$m_{k} = \begin{cases} \frac{1}{v_{k} \sum_{s=1}^{p} n_{s}} & \text{otherwise} \end{cases}$$

$$m_{k} \neq 0 \text{ and } \mathbf{x}(t) = \mathbf{0}$$

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$$m_{k} \neq 0 \text{ and$$

$$sign(z) = \begin{cases} 1 & \text{if } z > 0 \\ 0 & \text{otherwise} \end{cases}$$
 (30)

and
$$\sum_{i=1}^{p} \mathbf{Q}_{i} > \mathbf{0}$$
 (positive definite) for $i = 1, 2, ..., p$ (31)

It should be noted that the denominator $\sum_{k=1}^{p} sign(w_k)$ in (29)

will never be equal to zero as at least one of the w_k is greater than zero (a property of the fuzzy plant model). By choosing m_k , k = 1, 2, ..., p, according to (28) and (29), we can see that the property of (9) is satisfied. From (27) to (31) and considering the case that all $w_k \neq 0$, k = 1, 2, ..., p, such that

$$m_{k} = \frac{\hat{\mathbf{x}}(t)^{\mathsf{T}} \sum_{i=1}^{p} w_{i} \mathbf{Q}_{ik} \hat{\mathbf{x}}(t)}{w_{k} \sum_{s=1}^{p} \hat{\mathbf{x}}(t)^{\mathsf{T}} \sum_{i=1}^{p} w_{i} \mathbf{Q}_{is} \hat{\mathbf{x}}(t)}, \text{ then (27) becomes,}$$

$$m_{k} = \frac{\hat{\mathbf{x}}(t)^{\mathsf{T}} \sum_{i=1}^{p} w_{i} \mathbf{Q}_{is} \hat{\mathbf{x}}(t)}{w_{k} \sum_{s=1}^{p} \hat{\mathbf{x}}(t)^{\mathsf{T}} \sum_{i=1}^{p} w_{i} \mathbf{Q}_{is} \hat{\mathbf{x}}(t)}, \text{ then (27) becomes,}$$

$$V_{r}(\mathbf{e}(t)) = \frac{1}{2} e(t)^{\mathsf{P}} \mathbf{P}_{r} \mathbf{e}(t) \geq \frac{1}{2} \lambda_{\min}(\mathbf{P}_{r}) \|\mathbf{x}(t)\| \Rightarrow \frac{\lambda_{\min}(\mathbf{P}_{r})}{\lambda_{\min}(\mathbf{P}_{r})} \geq \|\mathbf{e}(t)\|^{\mathsf{T}} \|\mathbf{e}(t)\|^$$

From (31), as $\sum_{i=1}^{p} \mathbf{Q}_{ii}$, i = 1, 2, ..., p, are positive definite

matrices,
$$\frac{\sum_{j=1}^{p} \left(\sum_{i=1}^{p} w_{i} \hat{\mathbf{x}}(t)^{\mathsf{T}} \mathbf{Q}_{ij} \hat{\mathbf{x}}(t)\right)^{2}}{\sum_{j=1}^{p} \hat{\mathbf{x}}(t)^{\mathsf{T}} w_{i} \sum_{k=1}^{p} \mathbf{Q}_{ik} \hat{\mathbf{x}}(t)} \quad \text{in (32) is semi-positive}$$

$$\dot{V}_{p}(\mathbf{x}(t)) \le -\frac{1}{4} \lambda_{\min}(\mathbf{Q}_{p}) \|\mathbf{x}(t)\|^{2} + \left(\frac{\gamma^{2}}{\lambda_{\min}(\mathbf{Q}_{p})} + \|\mathbf{P}_{p}\mathbf{H}_{tt}\|_{\max}\right) \|\mathbf{e}(t)\|^{2}$$
 (33)

(33) will be used later. Then, we consider the state convergence ability of the fuzzy observer (3). We shall show that $\mathbf{e}(t) = \mathbf{x}(t) - \hat{\mathbf{x}}(t) \to \mathbf{0}$ as $t \to \infty$. Form (3) and (7),

$$\dot{\mathbf{c}}(t) = \dot{\mathbf{x}}(t) - \dot{\mathbf{x}}(t) = \sum_{i=1}^{p} w_i (\mathbf{A}_i \mathbf{x}(t) + \mathbf{B}_i \mathbf{u}(t)) - \sum_{j=1}^{p} w_j (\mathbf{A}_j \dot{\mathbf{x}}(t) + \mathbf{B}_j \mathbf{u}(t) + \mathbf{K}_j \mathbf{C}_j \mathbf{e}(t))$$

$$= \sum_{i=1}^{p} w_i (\mathbf{A}_i - \mathbf{K}_i \mathbf{C}_i) \mathbf{e}(t) = \sum_{j=1}^{p} w_j \mathbf{J}_j \mathbf{e}(t)$$

where
$$J_i = A_i - K_i C_i$$
, $i = 1, 2, ..., p$ (35)

(28) To study the stability of (34), consider the Lyapunov function:

$$V_{\epsilon}(\mathbf{e}(t)) = \frac{1}{2} \mathbf{e}(t)^{\mathrm{T}} \mathbf{P}_{\epsilon} \mathbf{e}(t)$$
 (36)

where $\mathbf{P}_{e} \in \Re^{n \times n}$ is a symmetric positive definite matrix.

$$\dot{V}_{\epsilon}(\mathbf{e}(t)) = \frac{1}{2} \left(\dot{\mathbf{e}}(t)^{\mathsf{T}} \mathbf{P}_{\epsilon} \mathbf{e}(t) + \mathbf{e}(t)^{\mathsf{T}} \mathbf{P}_{\epsilon} \dot{\mathbf{e}}(t) \right)$$
(37)

$$\dot{V}_{e}(\mathbf{e}(t)) = \frac{1}{2} \left[\left(\sum_{i=1}^{p} w_{i} \mathbf{J}_{i} \mathbf{e}(t) \right)^{\mathsf{T}} \mathbf{P}_{e} \mathbf{e}(t) + \mathbf{e}(t)^{\mathsf{T}} \mathbf{P}_{e} \left(\sum_{i=1}^{p} w_{i} \mathbf{J}_{i} \mathbf{e}(t) \right) \right]$$

$$= -\frac{1}{2} \sum_{i=1}^{p} w_i \mathbf{e}(t)^\mathsf{T} \mathbf{Q}_{e_i} \mathbf{e}(t) \le -\frac{1}{2} \max_{i} \lambda_{\min} \left(\mathbf{Q}_{e_i} \right) \left\| \mathbf{e}(t) \right\|^2 \tag{38}$$

where $\mathbf{Q}_{\epsilon_i} \in \Re^{n \times n}$, i = 1, 2, ..., p, are a symmetric positive

$$\mathbf{Q}_{e_i} = -\left(\mathbf{J}_i^{\mathsf{T}} \mathbf{P}_e + \mathbf{P}_e \mathbf{J}_i\right), i = 1, 2, ..., p$$
(39)

$$\max \lambda_{\min}(\mathbf{Q}_{\epsilon_i}) \ge \lambda_{\min}(\mathbf{Q}_{\epsilon_i}) > 0, i = 1, 2, ..., p \tag{40}$$

From (13), (36) and the property of (19), we have,

$$V_{p}(\mathbf{x}(t)) = \frac{1}{2} \mathbf{x}(t)^{\mathsf{T}} \mathbf{P}_{p} \mathbf{x}(t) \ge \frac{1}{2} \lambda_{\min} \left(\mathbf{P}_{p} \right) \| \mathbf{x}(t) \|^{2} \Rightarrow \frac{2V_{p}(\mathbf{x}(t))}{\lambda_{\min} \left(\mathbf{P}_{p} \right)} \ge \| \mathbf{x}(t) \|^{2}$$
 (41)

$$V_{\epsilon}(\mathbf{e}(t)) = \frac{1}{2} \mathbf{e}(t)^{\mathsf{T}} \mathbf{P}_{\epsilon}(t) \ge \frac{1}{2} \lambda_{\min} (\mathbf{P}_{\epsilon}) \|\mathbf{x}(t)\|^{2} \Rightarrow \frac{2V_{\epsilon}(\mathbf{e}(t))}{\lambda_{\min} (\mathbf{P}_{\epsilon})} \ge \|\mathbf{e}(t)\|^{2}$$
(42)

$$\begin{bmatrix} \dot{V}_{\rho}(\mathbf{x}(t)) \\ \dot{V}_{\epsilon}(\mathbf{e}(t)) \end{bmatrix} \leq \begin{bmatrix} -\frac{1}{2} \frac{\lambda_{\min}(\mathbf{Q}_{\rho})}{\lambda_{\min}(\mathbf{P}_{\rho})} & \frac{2}{\lambda_{\min}(\mathbf{P}_{\rho})} \begin{pmatrix} \frac{\gamma^{2}}{\lambda_{\min}(\mathbf{Q}_{\rho})} + \|\mathbf{P}_{\rho}\mathbf{H}_{a}\|_{\max} \\ -\frac{\max}{\lambda_{\min}(\mathbf{Q}_{\epsilon})} \end{pmatrix} \begin{bmatrix} V_{\rho}(\mathbf{x}(t)) \\ V_{\epsilon}(\mathbf{e}(t)) \end{bmatrix}$$
(43)

As
$$-\frac{1}{2} \frac{\lambda_{\min}(\mathbf{Q}_p)}{\lambda_{\min}(\mathbf{P}_p)}$$
 and $-\frac{\max_{i} \lambda_{\min}(\mathbf{Q}_{e_i})}{\lambda_{\min}(\mathbf{P}_e)}$ in (43) are both

$$\begin{bmatrix} -\frac{1}{2} \frac{\lambda_{\min}(\mathbf{Q}_{p})}{\lambda_{\min}(\mathbf{P}_{p})} & \frac{2}{\lambda_{\min}(\mathbf{P}_{e})} \left(\frac{\gamma^{2}}{\lambda_{\min}(\mathbf{Q}_{p})} + \left\| \mathbf{P}_{p} \mathbf{H}_{A} \right\|_{\max} \right) \\ 0 & -\frac{\max_{i} \lambda_{\min}(\mathbf{Q}_{e})}{\lambda_{\min}(\mathbf{Q}_{e})} \end{bmatrix}, \text{ it implies}$$

 $\begin{bmatrix} \dot{V}_p(\mathbf{x}(t)) \\ \dot{V}_e(\mathbf{e}(t)) \end{bmatrix} \leq \mathbf{0} \text{ [11]}. \text{ Hence, we can conclude that the fuzzy}$ observer-controller system of (11) is asymptotically stable, i.e. $\mathbf{x}(t) \to \mathbf{0}$ and $\mathbf{e}(t) \to \mathbf{0}$ as $t \to \infty$. The same result is

obtained under different cases of m_k , k = 1, 2, ..., p. It can be seen that in (43), the separation property holds, as the design of the fuzzy controller and observer can be achieved separately by finding P_p and P_e independently. The result and the design of the m_k are summarized into the following Lemma:

Lemma 1: A fuzzy observer-controller system formed by (3), (7) and (10) is guaranteed to be asymptotically stable if the following conditions are satisfied,

(i). There exists a solution P_p for the following (p+1) LMIs,

$$\begin{cases} \mathbf{Q} > \mathbf{0} \\ \sum_{s=1}^{p} \mathbf{Q}_{is} > \mathbf{0}, \ i = 1, 2, ..., p \end{cases}$$

where $\mathbf{Q} = -\mathbf{H}^{\mathsf{T}} \mathbf{P}_{p} - \mathbf{P}_{p} \mathbf{H}$, \mathbf{H} is a stable matrix, $\mathbf{Q}_{ik} = -\left(\mathbf{H}_{ik}^{\mathsf{T}} \mathbf{P} + \mathbf{P} \mathbf{H}_{ik}\right), \ \mathbf{H}_{ik} = \mathbf{A}_{i} + \mathbf{B}_{i} \mathbf{G}_{k} - \mathbf{H}.$

(ii). The gains of the fuzzy controller sub-controllers, m_k , k =1, 2, ..., p, are designed as follows,

$$m_{k} = \begin{cases} 1 & \text{if } w_{k} = 0 \\ \frac{n_{s}}{w_{k} \sum_{i=1}^{p} n_{s}} & \text{otherwise} \end{cases}$$

$$m_{s} = \begin{cases} \frac{1}{\sum_{k=1}^{p} sign(w_{k})} & w_{k} \neq 0 \text{ and } \mathbf{x}(t) = \mathbf{0} \\ \hat{\mathbf{x}}(t)^{\mathsf{T}} \sum_{i=1}^{p} w_{i} Q_{is} \hat{\mathbf{x}}(t) & \text{otherwise} \end{cases}$$

$$sign(z) = \begin{cases} 1 & \text{if } z > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$(iii) There exists a positive definite matrix $\mathbf{P}$$$

$$sign(z) = \begin{cases} 1 & \text{if } z > 0 \\ 0 & \text{otherwise} \end{cases}$$

(iii) There exists a positive definite matrix P. such that

$$\mathbf{Q}_{e_i} > \mathbf{0}$$
, $i = 1, 2, ..., p$, where $\mathbf{Q}_{e_i} = -\left(\mathbf{J}_i^T \mathbf{P}_e + \mathbf{P}_e \mathbf{J}_i\right)$, $\mathbf{J}_i = \mathbf{A}_i - \mathbf{K}_i \mathbf{C}_i$, $i = 1, 2, ..., p$, are stable matrices.

From Lemma 1, the total number of LMIs is 2p+1. The steps for finding the fuzzy observer-controller are as follows. Step I) Obtain the fuzzy plant model of the system.

Step II) Choose K_i , i = 1, 2, ..., p, for the fuzzy observer. Find P_p , by solving the p LMIs as stated in (iii) of Lemma 1. If P_e cannot be found, choose other K_i , i = 1, 2, ..., p.

Step III) Choose a stable matrix H and the G_k , k = 1, 2, ..., pfor the fuzzy controller. Find P_p by solving the p+1 LMIs as stated in (i) of Lemma 1. If P_{p} cannot be found, choose other **H** and G_k , k = 1, 2, ..., p, for the fuzzy controller.

Step IV). Design m_k , k = 1, ..., p, as stated in (ii) of Lemma 1.

IV. CONCLUSION

The stability of fuzzy observer-controller control systems has been analyzed. The stability conditions, which involve 2p+1 LMIs instead of (p(p+1)+2p)/2 LMIs, have been derived. A design methodology for the gains of the fuzzy controller has been given. The separation principle holds during the design of the observer and the controller.

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