



Letter to the Editor

## Comment on “Based on interval type-2 adaptive fuzzy $H^\infty$ tracking controller for SISO time-delay nonlinear systems”

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### ARTICLE INFO

#### Article history:

Received 30 March 2010

Accepted 28 May 2010

Available online 9 June 2010

#### Keywords:

Interval type-2 fuzzy neural network

Adaptive fuzzy controller

$H^\infty$  tracking performance

### ABSTRACT

In this comment, we point out the inappropriateness of Theorem 1 in the article [Tsung-Chih Lin, Mehdi Roopaei. Based on interval type-2 adaptive fuzzy  $H^\infty$  tracking controller for SISO time-delay nonlinear systems. Commun Nonlinear Sci Numer Simulat 2010;15:4065–75]. For solving this problem, some formular mistakes are corrected and novel parameter adaptive laws of interval type-2 fuzzy neural network system are given.

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### 1. Introduction

In [1], consider the  $n$ th-order time-delay system as follows:

$$\begin{cases} \dot{x}_i = x_{i+1}, & 1 \leq i \leq n-1, \\ \dot{x}_n = f(\mathbf{x}, \mathbf{x}(t-\tau_1), \dots, \mathbf{x}(t-\tau_r)) + g(\mathbf{x}, \mathbf{x}(t-\tau_1), \dots, \mathbf{x}(t-\tau_r))u(t) + d(t), \\ y = x_1, & t \in [-\tau, 0], \end{cases} \quad (1)$$

where  $f$  and  $g$  are unknown functions,  $u$  and  $y$  are control input and system output, respectively,  $\mathbf{x} = [x_1, \dots, x_n]$  is state vector, and  $d(t)$  is an external bounded disturbance. The tracking errors are defined as

$$e_i = y_{ri} - x_i, \quad i = 1, \dots, n, \quad (2)$$

where  $\mathbf{y}_r = [y_{r1}, \dots, y_{rn}]$  is the reference signal vector.

For approximating the unknown functions  $f$  and  $g$ , construct two interval type-2 fuzzy neural network (IT2-FNN) systems with the same fuzzy basic functions (FBFs) (from (24) and (25) of [1],  $\xi_f$  and  $\xi_g$  in (18) and (19) of [1] are equal to  $\xi$ ):

$$\hat{f}(\mathbf{x}, \tau | \theta_f, \mathbf{m}, \sigma) = \xi^T(\mathbf{x}, \tau, \mathbf{m}, \sigma) \theta_f, \quad (3)$$

$$\hat{g}(\mathbf{x}, \tau | \theta_g, \mathbf{m}, \sigma) = \xi^T(\mathbf{x}, \tau, \mathbf{m}, \sigma) \theta_g. \quad (4)$$

And give an indirect fuzzy controller scheme:

$$u = \frac{1}{\hat{g}(\mathbf{x}, \tau | \theta_g, \mathbf{m}, \sigma)} \left( -\hat{f}(\mathbf{x}, \tau | \theta_f, \mathbf{m}, \sigma) + y_r^{(n)} + \mathbf{k}^T \mathbf{e} - u_a \right), \quad (5)$$

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where real vector  $\mathbf{k} = [k_1, \dots, k_n]$  is chosen such that all roots of the polynomial  $p(s) = s^n + k_n s^{n-1} + \dots + k_1$  are in the open left half side of  $s$ -plane,  $\mathbf{e} = [e_1, \dots, e_n]$  is the error vector,  $u_a$  is a robust compensator. Then Theorem 1 in [1] shows that under controller (5) with the robust compensator (29) and adaptive laws (30)–(32) and (33) in [1], the  $H^\infty$  tracking performance of the system (1) can be achieved and all the variables of the closed-loop system are bounded.

However, we believe that using the same FBFs with identical adjusting parameters  $\mathbf{m}$  and  $\sigma$  in two IT2-FNN systems  $\hat{f}$  and  $\hat{g}$  is incorrect, because  $\hat{f}$  and  $\hat{g}$  are used to approximate two different objective functions. So the result of Theorem 1 in [1] is inappropriate. For solving this problem, in this paper, we redefine some variables of IT2-FNN and correct several formular mistakes in [1] firstly. And then, we present novel parameter adaptive laws for IT2-FNN systems.

## 2. Preliminary

For the convenience of analysis, we must redefine some variables and give correct expressions of IT2-FNN systems. According to [2,3], a Gaussian type interval type-2 fuzzy set (IT2-FS) can be expressed as

$$\mu_j(x_i) = \exp \left[ -\frac{1}{2} \frac{(x_i - m_{ij})^2}{(\sigma_{ij})^2} \right], \quad m_{ij} \in [\underline{m}_{ij}, \bar{m}_{ij}], \quad i = 1, \dots, n, \quad j = 1, \dots, s, \quad (6)$$

where  $m_{ij}$  and  $\sigma_{ij}$  are, respectively, the mean and the standard deviation of the Gaussian function in the  $j$ th term of the  $i$ th input  $x_i$ ,  $s$  is the number of the linguistic values with respect to  $x_i$ . Let  $\mathbf{m} = [m_{11}, \dots, m_{1s}, \dots, m_{n1}, \dots, m_{ns}]$ ,  $\sigma = [\sigma_{11}, \dots, \sigma_{1s}, \dots, \sigma_{n1}, \dots, \sigma_{ns}]$ . Then the IT2-FNN can be expressed as follows:

$$y(\mathbf{x}, \mathbf{m}, \sigma | \theta) = \xi^T(\mathbf{x}, \mathbf{m}, \sigma) \theta. \quad (7)$$

So according to (7), we can redefine  $\hat{f}$  and  $\hat{g}$  as

$$\hat{f}(\mathbf{x}, \tau | \theta_f, \mathbf{m}_f, \sigma_f) = \xi_f^T(\mathbf{x}, \tau, \mathbf{m}_f, \sigma_f) \theta_f, \quad (8)$$

$$\hat{g}(\mathbf{x}, \tau | \theta_g, \mathbf{m}_g, \sigma_g) = \xi_g^T(\mathbf{x}, \tau, \mathbf{m}_g, \sigma_g) \theta_g, \quad (9)$$

where subscripts  $f$  and  $g$  are used to distinguish the parameters of two different IT2-FNN systems.

## 3. Discussion

Define parameter errors as  $\tilde{\theta}_f = \theta_f - \theta_f^*$ ,  $\tilde{\theta}_g = \theta_g - \theta_g^*$ ,  $\tilde{\mathbf{m}}_f = \mathbf{m}_f - \mathbf{m}_f^*$ ,  $\tilde{\sigma}_f = \sigma_f - \sigma_f^*$ , where optimal parameter vectors  $\theta_f^*$ ,  $\mathbf{m}_f^*$  and  $\sigma_f^*$  are defined in (20)–(23) of [1]. Denoting  $\hat{f}(\mathbf{x}, \tau | \theta_f^*, \mathbf{m}_f^*, \sigma_f^*)$  by  $\hat{f}^*$  and making Taylor series expansion of  $\hat{f}^*$ , we obtain

$$\hat{f}^* = \hat{f} - \left. \frac{\partial \hat{f}}{\partial \theta_f} \right|_{\theta_f^*} \tilde{\theta}_f - \left. \frac{\partial \hat{f}}{\partial \mathbf{m}_f} \right|_{\mathbf{m}_f^*} \tilde{\mathbf{m}}_f - \left. \frac{\partial \hat{f}}{\partial \sigma_f} \right|_{\sigma_f^*} \tilde{\sigma}_f + \omega_f = \hat{f} - \xi_f^T \tilde{\theta}_f - \tilde{\mathbf{m}}_f \xi_{\mathbf{m}_f}^T \theta_f^* - \tilde{\sigma}_f \xi_{\sigma_f}^T \theta_f^* + \omega_f, \quad (10)$$

where  $\xi_{\mathbf{m}_f} = \partial \xi_f / \partial \mathbf{m}_f$ ,  $\xi_{\sigma_f} = \partial \xi_f / \partial \sigma_f$ , and  $\omega_f$  is the higher order term of the Taylor series. So we get

$$\begin{aligned} \hat{f} - \hat{f}^* &= \xi_f^T \tilde{\theta}_f + \tilde{\mathbf{m}}_f \xi_{\mathbf{m}_f}^T \theta_f^* + \tilde{\sigma}_f \xi_{\sigma_f}^T \theta_f^* + \omega_f = \xi_f^T \tilde{\theta}_f + \tilde{\mathbf{m}}_f \xi_{\mathbf{m}_f}^T \theta_f + \tilde{\sigma}_f \xi_{\sigma_f}^T \theta_f - \tilde{\mathbf{m}}_f \xi_{\mathbf{m}_f}^T \tilde{\theta}_f - \tilde{\sigma}_f \xi_{\sigma_f}^T \tilde{\theta}_f + \omega_f \\ &= \left( \xi_f^T - \mathbf{m}_f^* \xi_{\mathbf{m}_f}^T - \sigma_f^* \xi_{\sigma_f}^T \right) \tilde{\theta}_f + \left( \tilde{\mathbf{m}}_f \xi_{\mathbf{m}_f}^T + \tilde{\sigma}_f \xi_{\sigma_f}^T \right) \theta_f + \left( \mathbf{m}_f^* \xi_{\mathbf{m}_f}^T + \sigma_f^* \xi_{\sigma_f}^T \right) \tilde{\theta}_f + \omega_f. \end{aligned} \quad (11)$$

Similarly, denoting  $\partial \xi_g / \partial \mathbf{m}_g$  and  $\partial \xi_g / \partial \sigma_g$  by  $\xi_{\mathbf{m}_g}$  and  $\xi_{\sigma_g}$ , respectively, we have

$$\hat{g} - \hat{g}^* = \left( \xi_g^T - \mathbf{m}_g^* \xi_{\mathbf{m}_g}^T - \sigma_g^* \xi_{\sigma_g}^T \right) \tilde{\theta}_g + \left( \tilde{\mathbf{m}}_g \xi_{\mathbf{m}_g}^T + \tilde{\sigma}_g \xi_{\sigma_g}^T \right) \theta_g + \left( \mathbf{m}_g^* \xi_{\mathbf{m}_g}^T + \sigma_g^* \xi_{\sigma_g}^T \right) \tilde{\theta}_g + \omega_g. \quad (12)$$

Different from (35) and (36) in [1], (11) and (12) use subscripts  $f$  and  $g$  to distinguish two different IT2-FNN systems, and add superscript T to correct the mistake in (35) and (36) of [1].

According to (1) and (5), the last term of error dynamics (27) in [1] is redundant, that is, the error dynamic must be rewritten into

$$\dot{\mathbf{e}} = \mathbf{A}\mathbf{e} + \mathbf{B}[(\hat{f} - f) + (\hat{g} - g)u - d] + \mathbf{B}u_a, \quad (13)$$

$$\text{where } \mathbf{A} = \begin{bmatrix} 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \\ -k_n & -k_{n-1} & \cdots & -k_1 \end{bmatrix} \quad \text{and } \mathbf{B} = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix}.$$

Define optimal fuzzy approximation error as

$$\omega_{\text{opt}} = (\hat{f}^* - f) + (\hat{g}^* - g)u. \quad (14)$$

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