IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received October 25, 2017, accepted November 20, 2017, date of publication December 4, 2017, date of current version March 9, 2018.

Digital Object Identifier 10.1109/ACCESS.2017.2779118

Adaptive Fuzzy Control for Synchronization of Coronary Artery System With Input Nonlinearity

ZHANSHAN ZHAO[1], HAOLIANG CUI[1], JING ZHANG[2,3], AND JIE SUN[1]
[1]School of Computer Science and Software Engineering, Tianjin Polytechnic University, Tianjin 300387, China
[2]School of Textiles, Tianjin Polytechnic University, Tianjin 300387, China
[3]Tianjin Vocational Institute, Tianjin 300410, China

Corresponding author: Zhanshan Zhao (zhzhsh127@163.com)

This work was supported in part by the National Natural Science Foundation of China under Grant 61503280, Grant 61403278, and Grant 61471243, and in part by the Science and Technology Commission of Tianjin Municipality under Grant 15JCYBJC16100.

ABSTRACT In this paper, we propose a parametric adaptive control strategy for synchronization of Takagi–Sugeno (T-S) fuzzy coronary artery system. We use the T-S fuzzy model to represent the coronary artery system, because the coronary artery system has complicated nonlinear characteristic in reality. Based on the new model, a fuzzy parametric adaptive output feedback controller is designed to achieve the H_∞ synchronization of coronary artery system with input nonlinearity and parameter perturbations. Some simulation results are given to illustrate the effectiveness of our control strategy.

INDEX TERMS Coronary artery system, adaptive control, fuzzy model, input nonlinear, H_∞ synchronization.

I. INTRODUCTION

Chaos synchronization has been paid considerable attention among the scientists from biological engineering field such as epidemic diseases, nervous system and coronary artery system(CAS) [1], [2]. From the perspective of biology, CAS maintains our life by delivering oxygen and nutrition to myocardium. Once blood vessel of the coronary artery obstructed by thrombus, patients will suffering from a dangerous disease named myocardial infarction(MI). Therefore a lot of efforts have been done by the researchers among various areas. It's worth noting that Xu and Liu given the dynamics model of CAS in [3] which described CAS as a chaotic system:

$$\begin{aligned}\dot{x}_1(t) &= -bx_1(t) - cx_2(t),\\ \dot{x}_2(t) &= -(b+1)\omega x_1(t) - (c+1)\omega x_2(t) + \omega x_1^3(t)\\ &\quad + Ecos\sigma t \qquad (1)\end{aligned}$$

where $x_1(t), x_2(t)$ are the inner diameter and pressure changes of the coronary artery vessel, respectively. $Ecos\sigma t$ is used to describe the periodic perturbation.

Many existing works are based on the aforementioned model. In these researches, the treatment of MI are regarded as designing an appropriate control strategy to make the convulsionary vessel synchronize with a health one. In [4] and [5], backstepping approach and nonlinear state feedback method are used to the CAS synchronization. Reference [6] utilizes sliding mode control method to achieve synchronization of CAS under the bounded uncertainties, takes full account of the presence of disturbances in the actual coronary artery system. Furthermore, the CAS synchronization in finite-time is achieved using high-order sliding mode adaptive control method in [7], makes the convulsionary vessel synchronize with a health one in finite-time,to ensure the control effect in the actual coronary artery system timeliness. Considering the time delay caused by medication time and drug absorption, a chaotic synchronization feedback controller with input time-varying delay is design to guarantee the control performance of CAS in [8]. The above articles are effective in considering the actual problems of CAS.

However, the CAS has complicated nonlinear characteristics. The nonlinear term in (1) will loss some information of the system. In the past two decades, T-S fuzzy model exhibited significant functions in approximating and describing complex nonlinear systems [9]–[14]. In this paper, we give a fuzzy CAS model which can retain much more information of nonlinear characteristics. Therefore, the study on CAS base on T-S fuzzy model compared to the previous research results is closer to the actual CAS.

Nonlinear effect widely exist in the natural phenomenon. The absorption and diffusion of drugs is also a nonlinear effect. Therefore, the medical efficacy is regarded as a nonlinear inputs in our paper.Compared to [6], our study is closer to the actual CAS. Furthermore, the parameters uncertainties are considered in drive-response systems so that the research has stronger robustness. Recently, adaptive fuzzy feedback control approach [15]–[18] is proven to be effective in nonlinear system control. Previous studies on CAS relied on deterministic mathematical models. However, the existing model is the approximation of CAS, there is a certain error. For this reason, we design a fuzzy adaptive controller, so that in the case of nonlinear input signal, the coefficient matrix exists for the modeling uncertainty, the response system and the drive system to achieve synchronization. In recent years, the researchers have proposed some new control strategies based on adaptive control and fuzzy control for different nonlinear systems, such as adaptive fuzzy control [19]–[21], observer-based fuzzy adaptive output-feedback control [22], adaptive tracking Control [23]. Sliding mode control [24] and adaptive control are the general control theory of chaotic synchronization, there are some methods to combine sliding mode control, such as adaptive sliding mode control [25], optimal guaranteed cost sliding mode control [26], adaptive fuzzy hierarchical sliding mode control [27]. However, as we known, few researchers design control law based on fuzzy system which can better approach the real CAS with input nonlinearity and parameter perturbations.

Motivated by above discussions, we investigate the adaptive synchronization of CAS base on the T-S fuzzy model. An effective adaptive control strategy is proposed to the H_∞ synchronization of fuzzy CAS with the input nonlinear and parameter perturbations. The effectiveness of this strategy can be illustrated by the simulation in the following section.

A. CORONARY ARTERY FUZZY MODEL

In this paper, we use uncertain T-S fuzzy model to describe CAS as follows:

Plant rule k: IF $\phi_1(t)$ is $M_{k1}, \phi_2(t)$ is $M_{k2}, \cdots, \phi_r(t)$ is M_{kr}, THEN

$$\begin{aligned}\dot{x}_m(t) &= (A_k + \Delta A_k)x_m(t) + (B_k + \Delta B_k)p(x_m(t), t) \\ &\quad + q(t)(k = 1, \cdots, v) \\ y_m(t) &= Cx_m(t) \end{aligned} \tag{2}$$

where $\phi_j(t)(j = 1\cdots r)$ is the premise variable. $M_{ij}(i = 1\cdots k, j = 1\cdots r)$ is the fuzzy set. r represents the number of the fuzzy rule, $x_m(t), y_m(t) \in \mathbb{R}^n$ are the state vector and output vector, respectively. $p(x_m(t), t)$ is the nonlinear term. $q(t)$ denotes a perturbation with certain period. $A_k, B_k, C \in \mathbb{R}^{n*n}$ are constant real matrices. $\Delta A_k, \Delta B_k \in \mathbb{R}^{n*n}$ represent the uncertainties of system which can be described as:

$$[\Delta A_k, \Delta B_k] = HF(t)[E_{ak}, E_{bk}] \tag{3}$$

where $H, E_{ak}, E_{bk} \in \mathbb{R}^n$ are known constant matrices and $F(t)$ is an unknown matrix function satisfying: $F^T(t)F(t) \leq I$.

Using the singleton fuzzifier, product fuzzy inference and weighted average defuzzifier,the dynamic fuzzy model in (2) can be represented by:

$$\begin{aligned}\dot{x}_m(t) &= \sum_{k=1}^{v} h_k(\phi(t))\{(A_k + \Delta A_k)x_m(t) + (B_k + \Delta B_k) \\ &\quad *p(x_m(t), t) + q(t)\} \\ y_m(t) &= Cx_m(t) \end{aligned} \tag{4}$$

where $h_k(\phi(t)) = \frac{\prod_{j=1}^{r} M_{kj}(\phi_j(t))}{\sum_{k=1}^{v}\prod_{j=1}^{r} M_{kj}(\phi_j(t))}(k = 1, \cdots, v)$ is the normalized grade of membership and it satisfies: $\sum_{k=1}^{v} h_k(\phi(t)) = 1, h_k(\phi(t)) \geq 0$.

The fuzzy response system is given as follows:

Plant rule k: IF $\phi_1(t)$ is $M_{k1}, \phi_2(t)$ is $M_{k2}, \cdots, \phi_r(t)$ is M_{kr}, THEN

$$\begin{aligned}\dot{x}_s(t) &= (A_k + \Delta\tilde{A}_k(t))x_s(t) + (B_k + \Delta\tilde{B}_k(t))p(x_s(t), t) \\ &\quad + q(t) + d(t) + E\Omega(u(t))(k = 1, \cdots, v) \\ y_s(t) &= Cx_s(t) \end{aligned} \tag{5}$$

where $x_s(t), y_s(t) \in \mathbb{R}^n$ is the state vector and the output vector, respectively. $p(x_s(t), t)$ is the nonlinear term. $d(t)$ represents external disturbance. $E \in \mathbb{R}^{n*n}$ is constant real matrix. $\Delta\tilde{A}_k(t), \Delta\tilde{B}_k(t) \in \mathbb{R}^{n*n}$ denote the adaptive estimated value of $\Delta A_k, \Delta B_k$. Similar to (4), we infer the fuzzy response system (5) as:

$$\begin{aligned}\dot{x}_s(t) &= \sum_{k=1}^{v} h_k(\phi(t))\{(A_k+\Delta\tilde{A}_k(t))x_s(t)+(B_k+\Delta\tilde{B}_k(t)) \\ &\quad p(x_s(t), t) + q(t) + d(t)\} + E\Omega(u(t)) \\ y_s(t) &= Cx_s(t) \end{aligned} \tag{6}$$

Defining $e(t) = x_s(t) - x_m(t)$, the error system can be written as:

$$\begin{aligned}\dot{e}(t) &= \sum_{k=1}^{v} h_k(\phi(t))\{\Delta U_k x_s(t) + \Delta N_k p(x_s(t), t)\} \\ &\quad + \sum_{k=1}^{v} h_k(\phi(t))\{(A_k + \Delta A_k)e(t) + (B_k + \Delta B_k) \\ &\quad *p_e(t) + d(t)\} + E\Omega(u(t)) \end{aligned} \tag{7}$$

where

$$\Delta U_k = \Delta\tilde{A}_k(t) - \Delta A_k = (a_{kij})_{n\times n} \tag{8}$$

$$\Delta N_k = \Delta\tilde{B}_k(t) - \Delta B_k = (b_{kij})_{n\times n} \tag{9}$$

$$p_e(t) = p(x_s(t), t) - p(x_m(t), t) \tag{10}$$

The system (4) and (6) will be asymptotically synchronized if the synchronization error $e(t)$ satisfies $\lim_{t\to 0} e(t) = 0$. In this paper, we design an adaptive output feedback controller as follows:

$$u(t) = -\frac{\gamma(t)}{2}Ce(t) \tag{11}$$

where $u(t) = [u_1(t)\ldots u_n(t)]^T \in \mathbb{R}^n$ is the control input vector, $\Omega(u(t)) = \sum_{k=1}^{v} h_k(\phi(t))[\omega_1(u_1(t))\ldots\omega_n(u_n(t))]^T$

represents the nonlinear control input vector which satisfies the following inequality:

$$u_i(t)\omega_i(u_i(t)) \geq \nu_i(u_i(t))^2 \quad (1 \leq i \leq m) \tag{12}$$
$$\nu^* = min\nu_i \tag{13}$$

ω_i is function, $\gamma(t)$ is an adaptive parameter and adjusted by the following adaptive law:

$$\dot{\gamma}(t) = \nu^*\delta\|Ce(t)\|^2, \gamma(0) > 0. \tag{14}$$

where δ and ν are positive parameters. By applying of the above adaptive controller, synchronization error $e(t)$ will converge to zero asymptotically. To obtain the synchronization conditions, the following lemma and assumptions will be used during the proof.

Lemma 1 [28]: For a symmetric matrix Z and appropriately dimensional matrices D, G and $F(t)$ satisfying $F^T(t)F(t) < I$. Inequality $Z+He\{DF(t)G\} < 0$ is true, if and only if the following inequality $Z + \varepsilon DD^T + \varepsilon^{-1}GG^T < 0$ holds for any $\varepsilon > 0$.

Assumption 1: The nonlinear function $p(x(t); t)$ satisfies the Lipschitz condition:

$$|p(x_m(t), t) - p(x_s(t), t)| \leq |L(x_m(t) - x_s(t))| \tag{15}$$

where L is the Lipschitz constant matrix.

Assumption 2: Matrix $P > 0$ and satisfies the following equation:

$$E^T P = C \tag{16}$$

Remark 1: Assumption 1 is to deal with the nonlinear characteristics of chaotic systems. It is generally known that Assumption 2 is a matching condition in output feedback control of nonlinear systems,which is referenced in many papers [29], [30].

II. H_∞ SYNCHRONIZATION OF CAS

In this part, a parametric adaptive control strategy for synchronization of fuzzy CAS is proposed by utilizing above lemma and assumptions.

Theorem 1: Considering the fuzzy coronary artery drive and response systems (4) and (6), by applying the output feedback adaptive controller (11) with adaptive law (14), if existing symmetric positive definite matrix P and scalars α, ε_1 and $\varepsilon_2 > 0$ for given $\sigma > 0$, satisfying the following LMI:

$$\begin{bmatrix} \Gamma_1 & PB_k & -P & PH & PH & L^T \\ * & \Gamma_2 & 0 & 0 & 0 & 0 \\ * & * & -\sigma^2 I & 0 & 0 & 0 \\ * & * & * & -\varepsilon_1^{-1} I & 0 & 0 \\ * & * & * & * & -\varepsilon_2^{-1} I & 0 \\ * & * & * & * & * & -I \end{bmatrix} < 0 \tag{17}$$

where

$$\Gamma_1 = PA_k + A_k^T P + I - \alpha PEE^T P + \varepsilon_1^{-1} E_{ak}^T E_{ak}$$
$$\Gamma_2 = \varepsilon_2^{-1} E_{ak}^T E_{ak} - I \tag{18}$$

the attention rate σ for H_∞ synchronization in the disturbance situation can be achieved.

Proof: In this segment, the Lyapunov-Krasovskii functional can be constructed as follows:

$$V(t) = V_1(t) + V_2(t) \tag{19}$$

where

$$V_1(t) = e^T(t)Pe(t) + \int_0^t \sum_{k=1}^{v} h_k(\phi(s))\delta^{-1}\dot{\gamma}(s) *(\gamma(s) - \gamma^*)ds \tag{20}$$

$$V_2(t) = \sum_{k=1}^{v}\sum_{i=1}^{n}\sum_{j=1}^{n}[\frac{1}{2\theta_k}a_{kij}^2(t) + \frac{1}{2\varphi_k}c_{kij}^2(t)] \tag{21}$$

γ^* is a positive constants which will be defined later.

Taking the time derivative of $V(t)$:

$$\begin{aligned}\dot{V}_1(t) &= 2e^T(t)P\dot{e}(t) + \sum_{k=1}^{v} h_k(\phi(t))\delta^{-1}\dot{\gamma}(t)(\gamma(t) - \gamma^*) \\ &= \sum_{k=1}^{v} h_k(\phi(t))\Big\{e^T(t)\Big[PA_k + A_k^T P - \alpha PEE^T P\Big] \\ &\quad *e(t) + e^T(t)PHF(k)E_{ak}e(t) + e^T(t)E_{ak}^T F^T(k) \\ &\quad *H^T Pe(t) + e^T(t)B_k p_e(t) + p_e^T(t)B_k^T e(t) + e^T(t) \\ &\quad *PHF(k)E_{bk}p_e(t) + p_e^T(t)E_{bk}^T F^T(k)H^T Pe(t) \\ &\quad + \alpha\|E^T Pe(t)\|^2 + 2e^T(t)PE\Omega(u(t)) + \delta^{-1}\dot{\gamma}(\gamma(t) - \gamma^*) \\ &\quad - e^T(t)Pd(t) - d^T(t)Pe(t)\Big\} + 2e^T(t)P \\ &\quad * \sum_{k=1}^{v} h_k(\phi(t))\{\Delta U_k x_s(t) + \Delta N_k p(x_s(t), t)\}\end{aligned} \tag{22}$$

Utilizing (14), we can prove $\gamma(t)$ always remains positive. Assuming $Ce(t) = \Upsilon(t)_{m\times 1}$ and $\Upsilon_n(t)$ represents the $n - th$ element of $\Upsilon(t)$. Considering the following statements:

(1)If $\Upsilon_n(t) > 0$, it is easy to get $u_n(t) < 0$. Therefore, $\Upsilon_n(t)\omega_n(u_n(t)) \leq \nu_n\Upsilon_n(t)u_n(t)$ can be obtained by multiplying $\Upsilon_n(t)$ and dividing $u_n(t)$ by both sides of (11).

(2)If $\Upsilon_n(t) < 0$, it is easy to get $u_n(t) > 0$. Therefore, $\Upsilon_n(t)\omega_n(u_n(t)) \leq \nu_n\Upsilon_n(t)u_n(t)$ can be obtained by multiplying $\Upsilon_n(t)$, and dividing $u_n(t)$ by both side of (11).

We can find the following inequality will always holds:

$$\Upsilon_n(t)\omega_n(u_n(t)) \leq \nu_n\Upsilon_n(t)u_n(t). \tag{23}$$

Using Assumption 2 ,(11) and (23) we obtain:

$$\begin{aligned}2e^T(t)PE\Omega(\nu(t)) &= 2\sum_{n=1}^{m}\Upsilon_n(t)\omega_n(u_n(t)) \\ &\leq 2\sum_{n=1}^{m}\nu_n\Upsilon_n(t)u_n(t) \\ &\leq -\nu^*\gamma(t) \parallel Ce(t) \parallel^2\end{aligned} \tag{24}$$

Let $\alpha = \nu^*\gamma^*$, incorporating Assumption 1, (15) and (22), we have:

$$\begin{aligned}V_1(t) = \sum_{k=1}^{v} h_k(\phi(t))\Big\{e^T(t)\Big[PA_k + A_k^T P + L^T L - \alpha \\ *PEE^T P+(\varepsilon_1+\varepsilon_2)PHH^T P+\varepsilon_1^{-1}E_{ak}^T E_{ak}\Big]e(t) \\ + e^T(t)PB_k p_e(t) + p_e^T(t)B_k^T Pe(t) - e^T(t)Pd(t) \\ - d^T(t)Pe(t) + p_e^T(t)(\varepsilon_2^{-1}E_{ak}^T E_{ak} - I)p_e(t)\Big\} \\ + 2e^T(t)P\sum_{k=1}^{v} h_k(\phi(t))\{\Delta U_k x_s(t) + \Delta N_k p(x_s(t), t)\}\end{aligned} \tag{25}$$

Parametric adaptive laws are selected as follows:

$$\begin{aligned}\dot{a}_{1ij}(t) &= -h_1(\phi(t))\theta_1 l_i x_{sj}(t) \\ &\vdots \\ \dot{a}_{vij}(t) &= -h_v(\phi(t))\theta_v l_i x_{sj}(t) \\ \dot{b}_{1ij}(t) &= -h_1(\phi(t))\varphi_1 l_i p_j(x_{sj}(t), t) \\ &\vdots \\ \dot{b}_{vij}(t) &= -h_v(\phi(t))\varphi_v l_i p_j(x_{sj}(t), t)\end{aligned} \tag{26}$$

where l_i represents the $i-th$ element of $2e^T(t)P$. θ_v and φ_v are known constants. The time derivative of $V_2(t)$ can be written as follows:

$$\begin{aligned}\dot{V}_2(t) &= \sum_{k=1}^{v}\sum_{i=1}^{n}\sum_{j=1}^{n}\Big[\frac{1}{\theta_k}a_{kij}(t)\dot{a}_{kij}(t) + \frac{1}{\varphi_k}b_{kij}(t)\dot{b}_{kij}(t)\Big] \\ &= -\sum_{k=1}^{v}\sum_{i=1}^{n}\sum_{j=1}^{n} h_k(\phi(t))[a_{kij}(t)l_i x_{sj}(t) + b_{kij}(t) \\ &\quad *l_i p_j(x_{sj}(t), t)] \\ &= -2e^T(t)P\sum_{k=1}^{v} h_k(\phi(t))\{\Delta U_k x_s(t)+\Delta N_k p(x_s(t), t)\}\end{aligned} \tag{27}$$

Combining equations (25) and (27), we have:

$$\begin{aligned}\dot{V}(t) = \sum_{k=1}^{v} h_k(\phi(t))\Big\{e^T(t)\Big[PA_k + A_k^T P + L^T L - \alpha \\ PEE^T P + (\varepsilon_1 + \varepsilon_2)PHH^T P + \varepsilon_1^{-1}E_{ak}^T E_{ak}\Big]e(t) \\ + e^T(t)PB_k p_e(t) + p_e^T(t)B_k^T Pe(t) - e^T(t)Pd(t) \\ - d^T(t)Pe(t) + p_e^T(t)(\varepsilon_2^{-1}E_{ak}^T E_{ak} - I)p_e(t)\Big\}\end{aligned} \tag{28}$$

To investigate H_∞ performance, we define J as follows:

$$J = \int_o^\infty [e^T(t)e(t) - \sigma^2 d^T(t)d(t)]dt \tag{29}$$

Using zero initial condition, we have:

$$\begin{aligned}J &\le \int_o^\infty [\dot{V}(t) + e^T(t)e(t) - \sigma^2 d^T(t)d(t)]dt \\ &= \zeta^T(t)\Omega\zeta(t)\end{aligned} \tag{30}$$

where $\zeta^T(t) = [e^T(t) \quad p_e^T(t) \quad d^T(t)]$,

$$\Omega = \begin{bmatrix}\Gamma_1 & PB_k & -P \\ * & \varepsilon_2^{-1}E_{ak}^T E_{ak} - I & 0 \\ * & * & -\sigma^2 I\end{bmatrix}, \tag{31}$$

$$\begin{aligned}\Gamma_1 = PA_k + A_k^T P + I + L^T L - \alpha PEE^T P \\ + (\varepsilon_1 + \varepsilon_2)PHH^T P + \varepsilon_1^{-1}E_{ak}^T E_{ak}.\end{aligned} \tag{32}$$

when $\Omega < 0$, we can see that $J < 0$ and $\|e(t)\|_2 < \|d(t)\|_2$. Using Schur complement lemma, (31) can be transformed into (17), which completed the proof of Theorem 1.

Remark 2: Compared to the existing researches on chaotic synchronization of coronary artery system, our strategy fully considers input nonlinearity and parameter perturbations.

III. SIMULATION

The following numerical example is given to illustrate the effectiveness of our control strategy. Consider the T-S fuzzy coronary artery systems (4) and (6) with the following parameters:

$$\begin{aligned}A_1 = A_2 &= \begin{bmatrix}-0.15 & 1.7 \\ 0.575 & -0.35\end{bmatrix}, \quad B_1=B_2=\begin{bmatrix}0 & 0 \\ 0 & -0.5\end{bmatrix}, \\ C &= \begin{bmatrix}1.5 & 0 \\ 0 & 0.8\end{bmatrix}, \quad E=\begin{bmatrix}3 & 0 \\ 0 & 3\end{bmatrix}, \ H = \begin{bmatrix}1 & 0 \\ 0 & 2\end{bmatrix}, \\ E_{a1} &= \begin{bmatrix}-0.025 & 0.05 \\ 0.025 & -0.05\end{bmatrix}, \quad E_{a2}=\begin{bmatrix}0.025 & -0.05 \\ -0.025 & 0.05\end{bmatrix}, \\ E_{d1} &= \begin{bmatrix}0 & 0 \\ 0 & -0.1\end{bmatrix}, \quad E_{d2}=\begin{bmatrix}0 & 0 \\ 0 & 0.1\end{bmatrix}, \ L=\begin{bmatrix}1 & 0 \\ 0 & 2\end{bmatrix}, \\ F(t) &= \begin{bmatrix}0.5cos(t) & 0 \\ 0 & 0.5sin(t)\end{bmatrix}, \quad d(t)=\begin{bmatrix}0.05cos(3t) \\ 0.1cos(6t)\end{bmatrix}, \\ \Omega(u(t)) &= \begin{bmatrix}1 + 0.1sin(u_1(t))u_1(t) \\ 1 + 0.2cos(u_2(t))u_2(t)\end{bmatrix}, \sigma = 0.3.\end{aligned}$$

For the sake of analysis, we assume $\Delta N_k = 0$, $\theta_1 = 35$, $\theta_2 = 3$, The membership functions of the drive and response systems are selected as: $h_1(\phi(t)) = \frac{x_{m1}^2}{h^2}$, $h_2(\phi(t)) = 1 - \frac{x_{m1}^2}{h^2}$ and $h_1(\phi(t)) = \frac{x_{s1}^2}{h^2}$, $h_2(\phi(t)) = 1 - \frac{x_{s1}^2}{h^2}$ $(h^2 = 5)$, respectively. According to Theorem 1 and Assumption 2, we can get $P = diag\{0.5 \quad \frac{0.8}{3}\}$, $\alpha = 15.5336$, $\varepsilon_1 = 17.9871$, $\varepsilon_2 = 17.0300$. Initial value of system (4) and (6) are selected as:$(x_{m1}(0), x_{m2}(0)) = (1.5, -0.2)$ and $(x_{s1}(0), x_{s2}(0)) = (0.5, 0.8)$, respectively. The following figures can explain the effectiveness of our control strategy. Phase portrait of the CAS (4) under aforementioned parameters are shown in Figure 1(a), we can observe that the trajectory of CAS exhibits a significant chaotic behavior. The errors between system (4) and (6) with different initial value and without any control are shown in Figure 1(b). It is obvious that the drive-response systems are nonsynchronous. Time response of estimation errors are displayed in Figure1(c). We can see that the parameters of system (4) can't be estimated accurately. From Figure 2(c), we find that error systems can converge to zero by applying the proposed adaptive feedback controller which can be exhibited in Figure 2(a) and 2(b). Time response of

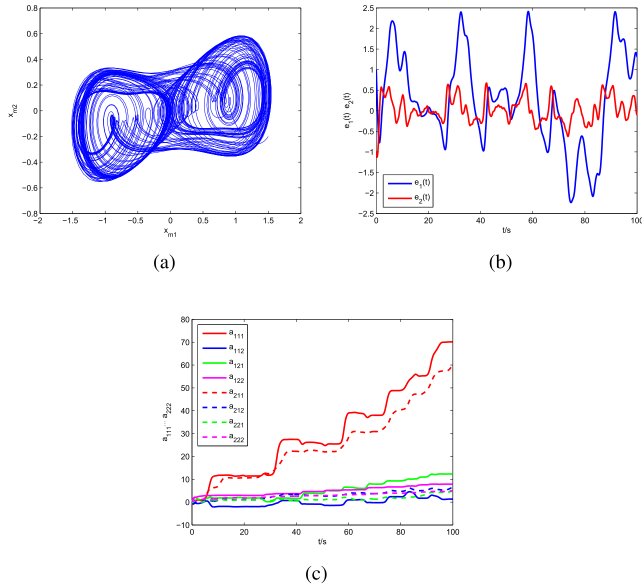


FIGURE 1. **Behavior of the CAS (4) and (6) without control. (a) phase portrait of drive system. (b) synchronization errors. (c) time response of parameters estimation errors.**

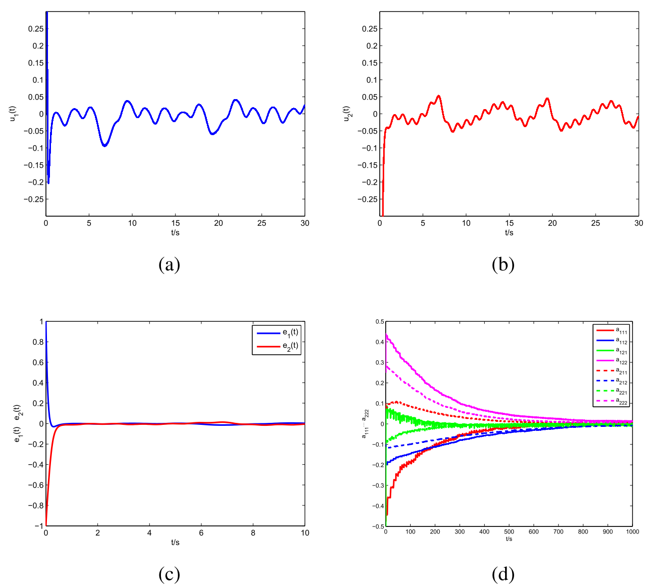


FIGURE 2. **Behavior of the CAS (4) and (6) with control. (a) control input signal $u_1(t)$. (b) control input signal $u_2(t)$. (c) synchronization errors. (d) time response of parameters estimation errors.**

parametric estimation errors are given in Figure2(d). We can clearly see that system (4) can be estimated accurately. Above simulations demonstrated the effectiveness of our synchronisation strategy under the input nonlinearity, parameters uncertainties and external disturbances.

IV. CONCLUSIONS

In this paper, we utilize T-S fuzzy model to describe the CAS and propose an adaptive synchronization strategy based on this model. To be more conformable to reality, the drug effect of CAS is regarded as input nonlinear and the parametric adaptive control method is used to reduce the influence of parameter perturbations. The effectiveness of our control strategy can be demonstrated by the simulations. We investigated the coronary artery system based on T-S fuzzy model. However, for the uncertainties in the membership functions, the control strategies of the T-S fuzzy systems can not handle it well. Recently, type-2 T-S fuzzy model has been widely studied to deal with uncertain parameters existing in the membership functions [26]. In the future, we will focus on the chaos synchronization of the coronary artery system based on the type-2 T-S fuzzy model.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests regarding the publication of this paper.

REFERENCES

[1] Q. Zhang, X. Xie, P. Zhu, H. Chen, and G. He, "Sinusoidal modulation control method in a chaotic neural network," *Commun. Nonlinear Sci. Numer. Simul.*, vol. 19, no. 8, pp. 2793–2800, 2014.

[2] L. Li, G.-Q. Sun, and Z. Jin, "Bifurcation and chaos in an epidemic model with nonlinear incidence rates," *Appl. Math. Comput.*, vol. 216, no. 4, pp. 1226–1234, 2010.

[3] Z. Xu and C. Liu, "The chaos phenomenon of the models for two types of muscular blood vessel," *J. Biomash*, vol. 1, no. 2, pp. 109–115, 1986.

[4] C.-Y. Gong, Y.-M. Li, and X.-H. Sun, "Backstepping control of synchronization for biomathematical model of muscular blood vessel," *J. Appl. Sci.*, vol. 24, no. 6, pp. 604–607, 2006.

[5] C.-Y. Gong, Y.-M. Li, and X.-H. Sun, "Nonlinear feedback synchronization control of the biomathematical model of muscular blood vessel," *Math. Pract. Theory*, vol. 38, no. 8, pp. 103–108, 2008.

[6] C.-J. Lin, S.-K. Yang, and H.-T. Yau, "Chaos suppression control of a coronary artery system with uncertainties by using variable structure control," *Comput. Math. Appl.*, vol. 64, no. 5, pp. 988–995, 2012.

[7] Z.-S. Zhao, J. Zhang, G. Ding, and D.-K. Zhang, "Chaos synchronization of coronary artery system based on higher order sliding mode adaptive control," *Acta Phys. Sinica*, vol. 64, no. 21, p. 210508, 2015.

[8] X.-M. Li, Z.-S. Zhao, J. Zhang, and L.-K. Sun, "H_∞ synchronization of the coronary artery system with input time-varying delay," *Chin. Phys. B*, vol. 25, no. 6, p. 060504, 2016.

[9] M. Bernal, T. M. Guerra, and A. Kruszewski, "A membership-function-dependent approach for stability analysis and controller synthesis of Takagi–Sugeno models," *Fuzzy Sets Syst.*, vol. 160, no. 19, pp. 2776–2795, 2009.

[10] K. Guelton, T.-M. Guerra, M. Bernal, T. Bouarar, and N. Manamanni, "Comments on fuzzy control systems design via fuzzy Lyapunov functions," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 40, no. 3, pp. 970–972, Jun. 2010.

[11] D. H. Lee, J. B. Park, and Y. H. Joo, "A fuzzy Lyapunov function approach to estimating the domain of attraction for continuous-time Takagi–Sugeno fuzzy systems," *Inf. Sci.*, vol. 185, no. 1, pp. 230–248, 2012.

[12] L. A. Mozelli and R. M. Palhares, "Stability analysis of Takagi–Sugeno fuzzy systems via LMI: Methodologies based on a new fuzzy Lyapunov function," *Sba, Controle Autom. Soc. Brasileira Autom.*, vol. 22, no. 6, pp. 664–676, 2011.

[13] H. Dong, Z. Wang, J. Lam, and H. Gao, "Fuzzy-model-based robust fault detection with stochastic mixed time delays and successive packet dropouts," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 42, no. 2, pp. 365–376, Apr. 2012.

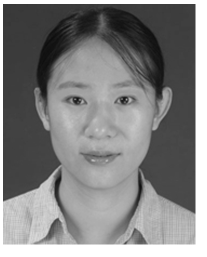
[14] P. Selvaraj, R. Sakthivel, and H. R. Karimi, "Equivalent-input-disturbance-based repetitive tracking control for Takagi–Sugeno fuzzy systems with saturating actuator," *IET Control Theory Appl.*, vol. 10, no. 15, pp. 1916–1927, 2016.

[15] Y.-J. Liu, Y. Gao, S. Tong, and Y. Li, "Fuzzy approximation-based adaptive backstepping optimal control for a class of nonlinear discrete-time systems with dead-zone," *IEEE Trans. Fuzzy Syst.*, vol. 24, no. 1, pp. 16–28, Feb. 2016.

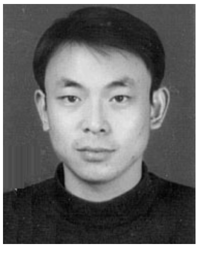
[16] S. Tong and Y. Li, "Adaptive fuzzy decentralized output feedback control for nonlinear large-scale systems with unknown dead-zone inputs," *IEEE Trans. Fuzzy Syst.*, vol. 21, no. 5, pp. 913–925, Oct. 2013.
[17] Y.-J. Liu, W. Wang, S.-C. Tong, and Y.-S. Liu, "Robust adaptive tracking control for nonlinear systems based on bounds of fuzzy approximation parameters," *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans*, vol. 40, no. 1, pp. 170–184, Jan. 2010.
[18] S. Tong, L. Zhang, and Y. Li, "Observed-based adaptive fuzzy decentralized tracking control for switched uncertain nonlinear large-scale systems with dead zones," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 46, no. 1, pp. 37–47, Jan. 2016.
[19] H. Wang, W. Liu, J. Qiu, and P. X. Liu, "Adaptive fuzzy decentralized control for a class of strong interconnected nonlinear systems with unmodeled dynamics," *IEEE Trans. Fuzzy Syst.*, to be published, doi: 10.1109/TFUZZ.2017.2694799.
[20] L. Wang, H. Li, Q. Zhou, and R. Lu, "Adaptive fuzzy control for nonstrict feedback systems with unmodeled dynamics and fuzzy dead zone via output feedback," *IEEE Trans. Cybern.*, vol. 47, no. 9, pp. 2400–2412, Sep. 2017.
[21] H. Li, L. Bai, Q. Zhou, R. Lu, and L. Wang, "Adaptive fuzzy control of stochastic nonstrict-feedback nonlinear systems with input saturation," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 47, no. 8, pp. 2185–2197, Aug. 2017.
[22] H. Wang, P. X. Liu, and P. Shi, "Observer-based fuzzy adaptive output-feedback control of stochastic nonlinear multiple time-delay systems," *IEEE Trans. Cybern.*, vol. 47, no. 9, pp. 2568–2578, Sep. 2017.
[23] X. Zhao, P. Shi, X. Zheng, and L. Zhang, "Adaptive tracking control for switched stochastic nonlinear systems with unknown actuator dead-zone," *Automatica*, vol. 60, pp. 193–200, Oct. 2015.
[24] Z. Feng and P. Shi, "Sliding mode control of singular stochastic Markov jump systems," *IEEE Trans. Autom. Control*, vol. 62, no. 8, pp. 4266–4273, Aug. 2017.
[25] H. Li, J. Wang, H. Du, and H. R. Karimi, "Adaptive sliding mode control for Takagi–Sugeno fuzzy systems and its applications," *IEEE Trans. Fuzzy Syst.*, to be published, doi: 10.1109/TFUZZ.2017.2686357.
[26] H. Li, J. Wang, L. Wu, H.-K. Lam, and Y. Gao, "Optimal guaranteed cost sliding mode control of interval type-2 fuzzy time-delay systems," *IEEE Trans. Fuzzy Syst.*, to be published, doi: 10.1109/TFUZZ.2017.2648855.
[27] X. Zhao, H. Yang, W. Xia, and X. Wang, "Adaptive fuzzy hierarchical sliding-mode control for a class of MIMO nonlinear time-delay systems with input saturation," *IEEE Trans. Fuzzy Syst.*, vol. 25, no. 5, pp. 1062–1077, Oct. 2016.
[28] I. R. Petersen and C. V. Hollot, "A Riccati equation approach to the stabilization of uncertain linear systems," *Automatica*, vol. 22, no. 4, pp. 397–411, 1986.
[29] C. Qian and W. Lin, "Output feedback control of a class of nonlinear systems: A nonseparation principle paradigm," *IEEE Trans. Autom. Control*, vol. 47, no. 10, pp. 1710–1715, Oct. 2002.
[30] M. Chen, D. Zhou, and Y. Shang, "A sliding mode observer based secure communication scheme," *Chaos Solitons Fractals*, vol. 25, no. 3, pp. 573–578, 2005.

ZHANSHAN ZHAO was born in 1980. He received the M.S. degree from the Harbin Institute of Technology in 2006 and the Ph.D. degree from Tianjin University in 2010. He is currently an Associate Professor with Tianjin Polytechnic University and a Visiting Scholar with RMIT University, Australia. His current research interests include time-delay systems, sliding mode control, and chaotic system.

HAOLIANG CUI was born in 1993. He received the B.E. degree from Xingtai University in 2016. He is currently pursuing the master's degree with the College of Computer Science and Software, Tianjin Polytechnic University. His research interests include fuzzy control, sliding mode control, and their applications.



JING ZHANG was born in 1979. She is currently pursuing the Ph.D. degree with Tianjin Polytechnic University. She is currently a Senior Experimentalist with the Tianjin Vocational Institute. Her research interests include control theory and application, and robust control.



JIE SUN was born in 1979. He received the B.E. degree and the M.S. degrees from Tianjin Polytechnic University in 2002 and 2005, respectively. He is currently a Lecturer with Tianjin Polytechnic University. His research interests include time-delay system control theory and fuzzy system control.