IMPROVED ADAPTIVE FEEDBACK LINEARIZATION CONTROL BASED ON FUZZY LOGIC FOR NONLINEAR SYSTEMS

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Abstract - Based on feedback linearization, an improved fuzzy adaptive controller has been developed for undefined nonlinear systems. Two major results are presented in this article. The first one is the strategy in designing the controller to avoid the singularity problem that usually appears in indirect control methods based on neural or fuzzy approximation. The second one is the enhancement of the controller, which enables the control system to operate smoothly under the effects of nonlinearity input. The stability of the control system with nonlinear control input in the adaptive feedback linearization control based on fuzzy logic has been proved by means of Lyapunov's theory of stability. Illustrative examples are employed to testify to outstanding features of the proposed control approach.

Key words - Adaptive control; feedback linearization control; fuzzy logic; nonlinearity input; nonlinear control; neural networks.

Tóm tắt - Dựa trên nền hồi tiếp tuyến tính hóa, chúng tôi phát triển bộ điều khiển mờ thích nghi cho đối tượng phi tuyến không xác định. Có hai kết quả chính trong bài báo này. Kết quả thứ nhất là chiến lược trong thiết kế bộ điều khiển nhằm tránh qua vấn đề suy biến thường xuất hiện trong các giải pháp điều khiển gián tiếp dựa trên xấp xỉ nơron hoặc xấp xỉ mờ. Kết quả thứ hai là tính năng tăng cường của bộ điều khiển cho phép hệ thống điều khiển hoạt động trơn tru dưới tác động của tín hiệu điều khiển phi tuyến. Tính ổn định của hệ thống điều khiển với tín hiệu điều khiển phi tuyến trong giải pháp điều khiển thích nghi hồi tiếp tuyến tính hóa dựa trên logic mờ được chúng tôi chứng minh dùng lý thuyết ổn định Lyapunov. Ví dụ minh họa được sử dụng để minh chứng cho các tính năng vượt trội của giải pháp điều khiển đề ra.

Từ khóa - Điều khiển thích nghi; điều khiển hồi tiếp tuyến tính hóa; logic mờ; tín hiệu vào phi tuyến; điều khiển phi tuyến; mạng nơron.

1. Introduction

Nowadays, fuzzy logic (FL) and neural networks (NNs) are considered as powerful tools for modeling and controlling highly uncertain, nonlinear, and complex systems due to universal approximations [1-3]. The direct and indirect adaptive control schemes are derived from incorporating the abilities of universal approximations of NNs (or FL) into adaptive control methods [3]. Either FL system or NNs are employed to simulate the behaviours of the ideal controller to meet the control objective in the direct adaptive control scheme [3-6]. Different from the direct adaptive control schemes, the indirect adaptive control scheme utilizes either the FL system or NNs to approximate the unknown nonlinear terms of model dynamics and constructs the control laws by using these approximations [3, 7-9]. Let us consider the SISO nonlinear system in the form of $y^{(r)} = f(\mathbf{x}) + g(\mathbf{x})u$, where $u \in \Re$ is the control input. In order to meet the control objectives, the authors [3, 10-12] followed the indirect adaptive control method to develop controllers which are in the form of $u = \frac{1}{\hat{g}(\mathbf{x},\theta_g)}\left(v(t) - \hat{f}(\mathbf{x},\theta_f\right)$, where $\hat{g}(\mathbf{x},\theta_g) \in \Re$ and $\hat{f}(\mathbf{x},\theta_f) \in \Re$ denote the parameterized approximations of the actual nonlinear functions, $f(\mathbf{x}) \in \Re$ and $g(\mathbf{x}) \in \Re$, respectively. Since the approximations, and $\hat{f}(\mathbf{x},\theta_f)$, derived from either the fuzzy logic system or neural networks, it does not guarantee that these approximations are bounded away from zero for all time t. Specifically, $\hat{g}(\mathbf{x},\theta_g)$ may tend to zero or be close to zero at some points in time. In this situation, the control signals become very large, which leads to uncontrollability of the controlled systems or even system damage. This problem is named the singularity problem which usually appears in indirect fuzzy adaptive control approaches. In addition, all the above-mentioned controllers use the ideal assumption of linear input in design. According to this assumption, the controlled systems cannot reflect the real situations because the control inputs may appear nonlinearly due to the physical limitations of some components in the systems. These nonlinear inputs may cause degradation for the systems or even make the systems unstable [13].

The above discussions motivate contributions of this article on designing the improved fuzzy-based adaptive control to overcome the singularity as well as allowing the controlled systems to run under the effects of input nonlinearity. In contrast to previous works, the novel modifications in controller design were given in this article. Specifically, the proposed fuzzy control law is given in the form of $u(t) = \frac{\hat{g}(\mathbf{x},t)}{\hat{g}^2(\mathbf{x},t)+\varepsilon}\left(-\hat{f}(\mathbf{x},t)+v(t)\right)$, where ε is a nonzero constant and chosen by designers. This ensures the nonzero value of the term $\hat{g}^2(\mathbf{x},t)+\varepsilon$, and therefore the singularity problem can avoid. Specifically, the real control inputs to the systems are produced by a nonlinear function $\varphi(u(t))$. This enables the controlled system to work well under the effects of input nonlinearity.

2. Problem Statement and Feedback Linearization Control Design

2.1. Problem Statement

Let us consider the n*th* order SISO nonlinear system whose control input is nonlinearly perturbed:

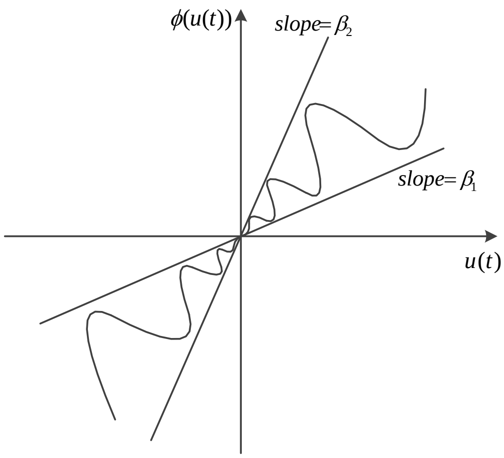

Figure 1. *The scalar nonlinear function* $\varphi(u(t))$

$$\begin{aligned}
&\dot{x}_1(t) = x_2(t),\\
&\dot{x}_2(t) = x_3(t),\\
&\dots \\
&\dot{x}_n(t) = f(\mathbf{x}) + g(\mathbf{x})\varphi(u(t)),\\
&y(t) = x_1(t),
\end{aligned} \tag{1}$$

where $\mathbf{x} = \begin{bmatrix} x_1(t) & x_2(t) & \dots & x_n(t) \end{bmatrix}^T \in \Re^n$ is the state vector. The functions, $f(\mathbf{x}) \in \Re$ and $g(\mathbf{x}) \in \Re$, are unknown smooth functions. $u(t) \in \Re$ is control input, while $y(t) \in \Re$ is system output. The function $\varphi(u(t))$ expresses the nonlinear control input. $\varphi(u(t))$ is assumed to be a continuous nonlinear function and inside the sector $[\beta_1 \quad \beta_2]$. β_1 and β_2 are nonzero positive constants and $\varphi(0) = 0$. The nonlinear function $\varphi(u(t))$ is depicted in Figure 1. We have the inequality:

$$\beta_1 u(t)^2 \le u(t)\varphi(u(t)) \le \beta_2 u(t)^2, \tag{2}$$

Without loss of generality and according to inequality (2), we assume that a continuous nonlinear function $g_u(u(t)) \in \Re$ exists, which is inside the sector $[\beta_1 \quad \beta_2]$ and satisfies $\varphi(u(t)) = g_u(u(t))u(t)$, then we have $\beta_1 u(t)^2 \le g_u(u(t))u(t)^2 \le \beta_2 u(t)^2$. Now we define a function $G(\mathbf{x}, u(t)) = g(\mathbf{x}) g_u(u(t))$, then the dynamic equations in (1) can be rewritten as follows:

$$\begin{aligned}
&\dot{x}_1(t) = x_2(t)\\
&\dot{x}_2(t) = x_3(t)\\
&\dots \\
&\dot{x}_n(t) = f(\mathbf{x}) + G(\mathbf{x}, u(t))u(t),\\
&y(t) = x_1(t).
\end{aligned} \tag{3}$$

The control goad is to design the control law $u(\mathbf{x}, t)$ such that the output $y(t) \in \Re$ tracks a given desired trajectory $y_d(t) \in \Re$ even if the nonlinear input exists. Based on feedback linearization control method [14], the ideal control law $u^*(\mathbf{x}, t)$ is given to meet the control objective as

$$u^*(\mathbf{x}, t) = \frac{1}{G(\mathbf{x}, u(t))}\left(-f(\mathbf{x}) + v(t)\right), \tag{4}$$

where $v(t) \in \Re$ is a new input and calculated according to the following equation:

$$v(t) = y_d^{(n)}(t) + \bar{e}_s(t) + \eta e_s(t), \tag{5}$$

where η is a positive designed constant. $e_s(t)$ and $\bar{e}_s(t)$ are defined as:

$$e_0(t) = y_d(t) - y(t), \tag{6}$$

$$e_s(t) = e_0^{(n-1)}(t) + k_1 e_0^{(n-2)}(t) + \dots + k_{n-1} e_0, \tag{7}$$

$$\bar{e}_s(t) = \dot{e}_s(t) - e_0^{(n)}(t) = k_1 e_0^{(n-1)}(t) + \dots + k_{n-1}\dot{e}_0, \tag{8}$$

where $e_0(t)$ is the tracking error, and the coefficients $k_1, k_2 \dots k_{n-1}$ are assigned such that $\Delta(s) = s^{(n-1)} + k_1 s^{(n-2)} + \dots + k_{n-2}s + k_{n-1}$ is a Hurwitz polynomial.

In this article, the functions $f(\mathbf{x}), G(\mathbf{x}, u(t))$ are completely unknown, so we need the following assumption for further stability analysis.

Assumption. $G(\mathbf{x}, u(t))s$ has the lower bound, a known positive constant $\underline{g}$, i.e., $0 < \underline{g} \le G(\mathbf{x}, u(t)) < \infty, \forall \mathbf{x} \in \Re^n$.

Substituting (4) into (3), one can get

$$\dot{x}_n = y^{(n)}(t) = v(t) = y_d^{(n)}(t) + \bar{e}_s(t) + \eta e_s(t). \tag{9}$$

By using (9) and (6), we obtain

$$e_0^{(n)}(t) + \bar{e}_s(t) + \eta e_s(t) = 0. \tag{10}$$

The error dynamics can be obtained by applying (8) to (10) as

$$\dot{e}_s(t) + \eta e_s(t) = 0. \tag{11}$$

The equation in (11) implies that both $e_s(t)$ and $e_0(t)$ converge to zero exponentially fast. Consequently, the controlled system is stable.

2.2. Description of a Fuzzy System

The fuzzy logic system is formed from four principal components: fuzzification, rule base, fuzzy inference and defuzzification. The fuzzification is the mapping process of n state variables, $x_1, x_2, \dots, x_n \in \Re$, to membership values. The rule base holds a set of IF-THEN rules that express the knowledge of the specialists in solving particular problems. The fuzzy inference is the mapping process of membership values from the input windows to the output window. The defuzzification is the mapping procedure from a set of inferred fuzzy signals contained within a fuzzy output window to a crisp signal. When center-average defuzzification is used, the outputs of a fuzzy logic system can present as [3].

$$\hat{f}(\mathbf{x}, t) = \frac{\sum_{i=1}^{m} \theta_{fi}(t)\left(\prod_{j=1}^{n} \mu_{A_j^i}(x_j)\right)}{\sum_{i=1}^{m}\left(\prod_{j=1}^{n} \mu_{A_j^i}(x_j)\right)} = \theta_f^T(t)\varphi(\mathbf{x}), \tag{12}$$

$$\hat{G}(\mathbf{x},t)=\frac{\sum_{i=1}^{m}\theta_{gi}(t)\left(\prod_{j=1}^{n}\mu_{A_j^i}(x_j)\right)}{\sum_{i=1}^{m}\left(\prod_{j=1}^{n}\mu_{A_j^i}(x_j)\right)}=\theta_g^T(t)\varphi(\mathbf{x}), \qquad (13)$$

where $\theta_f^T(t)=\left[\theta_{f1}(t)\quad \theta_{f2}(t)\quad ...\quad \theta_{fm}(t)\right]$ and $\theta_g^T(t)=\left[\theta_{g1}(t)\quad \theta_{g2}(t)\quad ...\quad \theta_{gm}(t)\right]$ are weighting vectors that are adjusted due to the adaptive laws. The parameters θ_{fi} and θ_{gi} with $i=1, 2,...,m$ are the points where the fuzzy singletons $\mu_{B_f^i}$ and $\mu_{B_g^i}$ reach their maximum values, i.e., $\mu_{B_f^i}(\theta_{fi})=\mu_{B_g^i}(\theta_{gi})=1$. The fuzzy basic vector $\varphi^T(\mathbf{x})=\left[\varphi_1(\mathbf{x})\quad \varphi_2(\mathbf{x})\quad ...\quad \varphi_m(\mathbf{x})\right]$ has m elements.

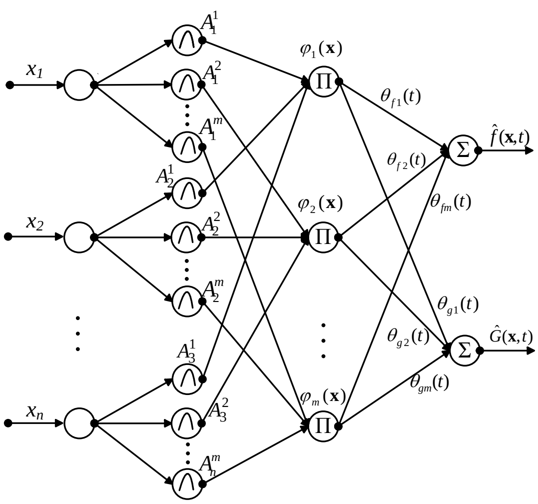

Figure 2. *The structure of a fuzzy neural network*

When a fuzzy logic system is combined with a neural network, a fuzzy neural network is establbished [3]. The fuzzy neural network is given in Figure 2.

3. Fuzzy-Based Adaptive Feedback Linearization Control

When $f(\mathbf{x})$ and $G(\mathbf{x},u(t))$ are completely unknown, the ideal control law in (4) cannot be determined. To take care of this problem, the functions, $f(\mathbf{x})$ and $G(\mathbf{x},u(t))$, are approximated by a fuzzy neural network. Then using the certainty equivalent approach, the adaptive controller $u_{ac}(t)$ based on the feedback linearization, can be achieved as

$$u_{ac}(t)=\frac{1}{\hat{G}(\mathbf{x},t)}\left(-\hat{f}(\mathbf{x},t)+v(t)\right), \qquad (14)$$

where $\hat{f}(\mathbf{x},t)$ and $\hat{G}(\mathbf{x},t)$ are approximations of the functions $f(\mathbf{x})$ and $G(\mathbf{x},u(t))$ respectively.

However, the control law in (14) may fall into the singularity problem when $\hat{G}(\mathbf{x},t)$ is close to zero or even receives the zero value in some point in the initial period. This problem causes the control signal $u_{ac}(t)$ to get very large values. In such a situation, the closed-loop controlled system may lose controllability. To avoid this problem, we replace the control law in (14) with

$$u_{ac}(t)=\frac{\hat{G}(\mathbf{x},t)}{\hat{G}^2(\mathbf{x},t)+\varepsilon}\left(-\hat{f}(\mathbf{x},t)+v(t)\right), \qquad (15)$$

where ε is a designed nonzero constant. The constant ε is added to ensure that the term $\hat{G}^2(\mathbf{x},t)+\varepsilon$ is always nonzero. Therefore, the singularity problem can be avoided with this strategy. The approximations, $\hat{f}(\mathbf{x},t)$ and $\hat{G}(\mathbf{x},t)$, are calculated by means of a fuzzy neural network as

$$\hat{f}(\mathbf{x},t)=\theta_f^T(t)\varphi(\mathbf{x}), \qquad (16)$$

$$\hat{G}(\mathbf{x},t)=\theta_g^T(t)\varphi(\mathbf{x}), \qquad (17)$$

where $\theta_f(t)$ and $\theta_g(t)$ are weighting vectors at the output layer of the neural network shown in Figure 2. $\varphi(\mathbf{x})$ is a fuzzy basic vector. In the adaptive laws, $\theta_f(t)$ and $\theta_g(t)$ are online changed so that $\hat{f}(\mathbf{x},t)$ and $\hat{G}(\mathbf{x},t)$ converge to $f(\mathbf{x})$ and $G(\mathbf{x},u(t))$ respectively. When the controller runs, the values of weighting vectors $\theta_f(t)$ and $\theta_g(t)$ vary in accordance with the designed adaptive laws as follows:

$$\dot{\theta}_f(t)=-\mathbf{W}_f^{-1}\varphi(\mathbf{x})e_s(t), \qquad (18)$$

$$\dot{\theta}_g(t)=-\mathbf{W}_g^{-1}\varphi(\mathbf{x})u_{ac}(t)e_s(t), \qquad (19)$$

where $\mathbf{W}_f\in\Re^{m\times m}$ and $\mathbf{W}_g\in\Re^{m\times m}$ are positive-definite weighting matrices.

However, because $\hat{f}(\mathbf{x},t)$ and $\hat{G}(\mathbf{x},t)$ are approximated by a neural network, the approximation errors always exist. Let $\delta_f(\mathbf{x})$ and $\delta_g(\mathbf{x})$ be the approximation errors. We suppose that the approximation errors of the neural network are bounded.

Assumption 2. The approximation errors are upper bounded by some known constants $\bar{\delta}_f>0$ and $\bar{\delta}_g>0$ over the compact set $\Omega\subset\Re^n$; that is,

$$\sup_{x\in\Omega}\left|\delta_f(x)\right|\le\bar{\delta}_f, \qquad (20)$$

$$\sup_{x\in\Omega}\left|\delta_g(x)\right|\le\bar{\delta}_g. \qquad (21)$$

In order to reduce the undesirable effects of the approximation errors and keep the system in robustness, a compensatory controller $u_{cc}(t)s$ is used. The compensatory controller $u_{cc}(t)$ is given as

$$u_{cc}(t)=\frac{1}{\underline{g}}\left(\bar{\delta}_f+\bar{\delta}_g\left|u_{ac}(t)\right|+\left|u_{ec}(t)\right|\right)\mathrm{sgn}(e_s(t)), \qquad (22)$$

where $u_{ec}(t)=\frac{\varepsilon}{\hat{G}^2(\mathbf{x},t)+\varepsilon}\left(-\hat{f}(\mathbf{x},t)+v(t)\right)$

Therefore, the total control signals consist of two control terms: the fuzzy neural controller $u_{ac}(t)$ and the compensatory controller $u_{cc}(t)$. The total control signal can be expressed as

$$\begin{aligned} u(t) &= u_{ac}(t) + u_{cc}(t) \\ &= u_{ac}(t) + \frac{1}{\underline{g}}\left(\bar{\delta}_f + \bar{\delta}_g\left|u_{ac}(t)\right| + \left|u_{ec}(t)\right|\right)\operatorname{sgn}(e_s(t)) \end{aligned} \tag{23}$$

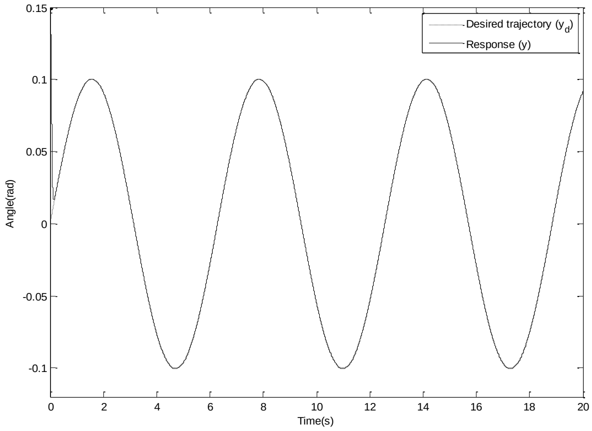

Figure 3. *Tracking performance of the system under the control action*

Theorem 1

Consider the nonlinear system (3), the control law (23), and the adaptive laws (18), (19). If the assumptions 1, 2 hold, then the tracking errors converge to zero asymptotically fast and therefore the system output tracks the desired trajectory successfully.

Proof. Consider the Lyapunov function $V(\mathbf{x},t)$ as below:

$$V(\mathbf{x},t) = \frac{1}{2}e_s^2(t) + \frac{1}{2}\tilde{\theta}_f^T(t)\mathbf{W}_f\tilde{\theta}_f(t) + \frac{1}{2}\tilde{\theta}_g^T(t)\mathbf{W}_g\tilde{\theta}_g(t). \tag{24}$$

We take some basic algebraic manipulations and obtain

$$\dot{V}(\mathbf{x},t) \le -\eta e_s^{\,2}(t) \;\le 0 \tag{25}$$

The inequality (25) implies that the nonlinear system with the designed controller is stable.

4. Numerical simulation

Let us consider the inverted pendulum system. x_1 is the angle of the pendulum with respect to the vertical line and x_2 expresses the angular velocity. The dynamic equations of the inverted pendulum system are given as [15].

$$\begin{aligned} \dot{x}_1 &= x_2, \\ \dot{x}_2 &= f(\mathbf{x}) + g(\mathbf{x})\varphi(u(t)), \\ y &= x_1, \end{aligned} \tag{26}$$

where

$$f(\mathbf{x}) = \frac{mlx_2\sin x_1\cos x_1 - (M+m)g_m\sin x_1}{ml\cos^2 x_1 - \frac{4}{3}l(M+m)},$$

$$g(\mathbf{x}) = \frac{-\cos x_1}{ml\cos^2 x_1 - \frac{4}{3}l(M+m)}.$$

$\mathbf{x} = \begin{bmatrix} x_1 & x_2 \end{bmatrix}^T$ is the state vector, while $y = x_1$ is the output of the system. The nonlinear function $\varphi(u(t)) = g_u(u(t))u(t)$ is the nonlinear control input. Let $G(\mathbf{x},u(t)) = g_u(u(t))g(\mathbf{x})$ and assume that $g_u(u(t)) = (1+0.2\sin(u(t)))$. The sinusoidal term in the $g_u(u(t))$ represents the nonlinear perturbation of the control signal. Now the dynamic equations of the inverted pendulum system can be rewritten as follows:

$$\begin{aligned} \dot{x}_1 &= x_2, \\ \dot{x}_2 &= f(\mathbf{x}) + G(\mathbf{x},u(t))u(t), \\ y &= x_1, \end{aligned} \tag{27}$$

where

$$G(\mathbf{x},u(t)) = g_u(u(t))g(\mathbf{x}) = \frac{-\cos x_1\left(1+0.5\sin(u(t))\right)}{ml\cos^2 x_1 - \frac{4}{3}l(M+m)}.$$

Since $f(\mathbf{x})$ and $G(\mathbf{x},u(t))s$ are considered as unknown functions, they are approximated by $\hat{f}(\mathbf{x},t)$ and $\hat{G}(\mathbf{x},t)$ via a fuzzy neural network. The designed fuzzy neural network has 2 inputs, which are x_1 and x_2. The membership layer is made up of 18 units with Gaussian functions, while the rule layer has 9 units.

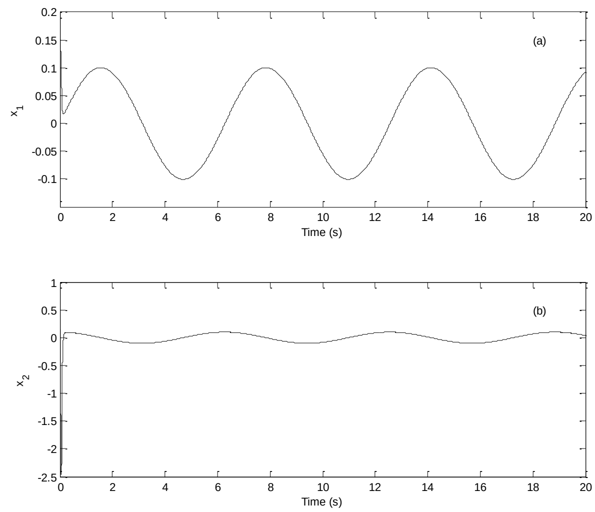

Figure 4. *State variables x_1 and x_2 during the simulation*

The control problem is to design the control law $u(t)$ such that the output $y(t)s$ tracks the desired trajectory $y_d(t)$ as close as possible. To meet the control objective and overcome the singularity problem, the improved adaptive control law was used as:

$$u_{ac}(t) = \frac{\hat{G}(\mathbf{x},t)}{\hat{G}^2(\mathbf{x},t)+\varepsilon}\left(-\hat{f}(\mathbf{x},t) + v(t)\right). \tag{38}$$

The remaining controller's components, $u_{cc}(t)$ and $u_{ec}(t)$, are designed in accordance with (15) and (22).

The desired trajectory $y_d(t) = 0.1\sin(t)$ is given to study the tracking performance of the controlled system. The state vector $\mathbf{x}(t)$ starts with $\mathbf{x}(0) = \begin{bmatrix} 0.15 & 0.15 \end{bmatrix}^T$ for the simulation. Figure 3 shows the tracking performance. Under the action of the designed controllers, the system output $y = x_1$ follows the desired trajectory $y_d(t) = 0.1\sin(t)$ successfully. Figure 4 describes the values of the state variables x_1, x_2 during the simulation.

5. Conclusions

In this article, based on a fuzzy neural network, the improved adaptive feedback linearization control approach has been developed for a class of SISO nonlinear systems subjected to nonlinear inputs. The designed controller can guarantee the perfect tracking performance where the tracking error converges to the origin even if the unknown models exist in the system. In addition, the improvement in the controller design enables the proposed controller to definitely avoid the singularity problem which can be considered as a serious drawback in the indirect adaptive control approach based on fuzzy or neural networks approximations.

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REFERENCES

[1] O. Castillo, J. R. Castro, P. Melin, and A. Rodriguez-Diaz, "Universal Approximation of a Class of Interval Type-2 Fuzzy Neural Networks in Nonlinear Identification," *Advances in Fuzzy Systems,* vol. 2013, p. 16, 2013.

[2] D. Driankov and R. Palm, *Advances in fuzzy control*: Physica-Verlag, 2013.

[3] L. X. Wang, *A Course in Fuzzy Systems and Control*: Prentice Hall PTR, 1997.

[4] M. Chemachema, "Output feedback direct adaptive neural network control for uncertain SISO nonlinear systems using a fuzzy estimator of the control error," *Neural networks,* vol. 36, pp. 25-34, 2012.

[5] N. Wang, J.-C. Sun, and Y.-C. Liu, "Direct adaptive self-structuring fuzzy control with interpretable fuzzy rules for a class of nonlinear uncertain systems," *Neurocomputing,* vol. 173, Part 3, pp. 1640-1645, 2016.

[6] Y. Pan, M. J. Er, Y. Liu, L. Pan, and H. Yu, "Composite Learning Fuzzy Control of Uncertain Nonlinear Systems," *International Journal of Fuzzy Systems,* vol. 18, pp. 990-998, 2016.

[7] O. Cerman and P. Hušek, "Adaptive fuzzy sliding mode control for electro-hydraulic servo mechanism," *Expert Systems with Applications,* vol. 39, pp. 10269-10277, 2012.

[8] W.-S. Yu and C.-C. Weng, "An observer-based adaptive neural network tracking control of robotic systems," *Applied Soft Computing,* vol. 13, pp. 4645-4658, 2013.

[9] B. Xu, F. Sun, Y. Pan, and B. Chen, "Disturbance Observer Based Composite Learning Fuzzy Control of Nonlinear Systems with Unknown Dead Zone," *IEEE Transactions on Systems, Man, and Cybernetics: Systems,* vol. PP, pp. 1-9, 2016.

[10] N. Mendes and P. Neto, "Indirect adaptive fuzzy control for industrial robots: A solution for contact applications," *Expert Systems with Applications,* vol. 42, pp. 8929-8935, 2015.

[11] W. Shi, "Observer-based indirect adaptive fuzzy control for SISO nonlinear systems with unknown gain sign," *Neurocomputing,* vol. 171, pp. 1598-1605, 2016.

[12] T.-B.-T. Nguyen, T.-L. Liao, and J.-J. Yan, "Adaptive tracking control for an uncertain chaotic permanent magnet synchronous motor based on fuzzy neural networks," *Journal of Vibration and Control,* July 8, 2013.

[13] J.-J. Yan, "Sliding mode control design for uncertain time-delay systems subjected to a class of nonlinear inputs," *International Journal of Robust and Nonlinear Control,* vol. 13, pp. 519-532, 2003.

[14] J. J. E. Slotine and W. Li, *Applied Nonlinear Control*. Taipei, Taiwan: Pearson Education Taiwan, 2005.

[15] S. Tong, H.-X. Li, and W. Wang, "Observer-based adaptive fuzzy control for SISO nonlinear systems," *Fuzzy Sets and Systems,* vol. 148, pp. 355-376, 2004.

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