2020 IEEE 9th Data Driven Control and Learning Systems Conference
November 20-22, 2020, Liuzhou, China

Observer-Based Adaptive Multi-dimensional Taylor Network Control for Nonlinear Systems with Time-Delay

Lei Chu[1,4], Shuhua Zhang[1,4], Mingxin Wang[1,4] , Shanliang Zhu[1,2,4*] , Yuqun Han[1,3,4]

1. School of Mathematics and Physics, Qingdao University of Science and Technology, Qingdao, 266061, P. R. China

2. College of Electromechanical Engineering, Qingdao University of Science and Technology, Qingdao, 266061, P. R. China

3. Key Laboratory of Measurement and Control of Complex Systems of Engineering, Ministry of Education, Nanjing, 210096, P. R. China

4. The Research Institute for Mathematics and Interdisciplinary Sciences, Qingdao University of Science and Technology, Qingdao 266061, China.

E-mail: zhushanliang@qust.edu.cn

Abstract: In this paper, an observer-based adaptive Multi-dimensional Taylor network (MTN) controller is proposed for strictly feedback nonlinear systems with time-delay and unmeasurable states. MTNs are utilized to approximate the unknown and desired control input signals directly instead of the unknown nonlinear functions. Moreover, a linear state observer is designed for estimating the unmeasured states. Based on the backstepping technique, a novel adaptive MTN control strategy with simple structure and good real time property is proposed. The designed controller can guarantee all the signals of the closed-loop system are bounded and the tracking error converges to a small neighborhood of the origin. Simulation results are given to demonstrate the effectiveness of the proposed method.

Key Words: Multi-dimensional Taylor network, Nonlinear systems, Adaptive control, Output-feedback, Backstepping

1 Introduction

As we all know, the stability analysis and controller design of nonlinear system have been active topics in recent decades and many advanced control methods have been proposed, such as adaptive control [1], fuzzy control [2], backstepping control [3], sliding mode control[4] and neural network control [5]. Especially, the adaptive backstepping control method [6-9] has received increasing attention, which has the ability to adjust the adaptive parameters by online learning. In addition, with the favorite approximation property, the issues of utilizing neural networks (NNs) and fuzzy logic systems (FLSs) to handle unknown nonlinear systems have been well investigated. Combining NNs or FLSs with adaptive backstepping control scheme, remarkable results have been reported [10-13]. And this design has been extended to different nonlinear systems such as strict-feedback nonlinear systems [10], switched nonlinear systems [11], large-scale nonlinear systems [12] and MIMO nonlinear systems [13]. However, it is worth noting that with the increase of the order of nonlinear system and the number of neural network nodes, the amount of parameters adjusted online increases dramatically, which greatly increases the calculation burden. Meanwhile, the drawbacks of FLSs are that it is difficult to get fuzzy rules and membership functions. Therefore, in order to overcome the above problems, an approximate control method based on MTN is proposed.

MTN is a three-layer forward network composed of input layer, middle layer and output layer. It uses a form similar to Taylor series expansion to perform high-order expansion of the input signal with a specified power, so that the controller has good approximation ability. In addition, the MTN-based controller has the advantages of good real-time performance, simple structure and easy engineering implementation [14-15]. Moreover, this network can be easily combined with other control methods such as adaptive control and backstepping control. Therefore, many nonlinear intelligent control strategies have been proposed [14-20]. At present, adaptive backstepping control based on MTN has been successfully extend to different nonlinear systems, such as SISO nonlinear system [15, 16], MIMO output feedback nonlinear systems [17], stochastic nonlinear systems [18, 19] and large-scale nonlinear systems [20]. However, the application of MTN control method is still in its infancy, and there are many issues to discuss. In particular, the adaptive MTN control strategy for time-delay nonlinear systems has not been studied.

On the other hand, time-delay is often encountered in practical engineering systems, which is usually the root of destroying system stability and reducing system performance. Therefore, the controller design of this kind of systems has been drawn more and more attention. In order to deal with time-delay of nonlinear systems, the common method is to choose the appropriate Lyapunov functions, which can compensate for the delay terms. In recent years, some scholars have proposed adaptive NNs or FLSs control methods to solve the problem of time-delay in nonlinear systems [21-24]. However, the current research only take the time delay in the system output into consideration, without considering the time delay in the state variables. Therefore, the control method proposed in [23] can not be applied to nonlinear systems with time-delay in state variables.

Motivated by the above observation, we study a class of strictly feedback nonlinear systems with time-delay. MTN is used to approximate the input signal and an observer is designed to estimate the unknown states. Compared with

978-1-7281-5922-5/20/$31.00 ©2020 IEEE DDCLS'20

the existing results, the main advantages of the proposed control method are as follows:

(1) In the process of controller design, time-delay exists not only in the system output, but also in the state variables, which makes the results of this paper more common in practical engineering.

(2) Based on the observer design, the MTN adaptive control method is successfully applied to the time-delay nonlinear system. The control scheme has the advantages of simple structure, small calculation and good real-time performance, which ensures that all signals of the closed-loop system are bounded and the tracking error tends to the origin.

2 Problem Formulation and Preliminaries

Consider the nonlinear system

$$\begin{cases} \dot{x}_i(t) = x_{i+1}(t) + f_i(\bar{x}_i(t)) + h_i(\bar{x}_i(t-\tau_i)) \\ \dot{x}_n(t) = u + f(x(t)) + h_n(x(t-\tau_n)) \\ y(t) = x_1(t), 1 \le i < n \end{cases} \quad (1)$$

where $\bar{x}_i(t) = [x_1(t), x_2(t), \cdots, x_i(t)]^{\mathrm{T}} \in R^i \quad (x = \bar{x}_n(t))$, $i = 1, \cdots, n$, $y \in R$ represent the control input and output of the system. $f_i(\cdot)$ and $h_i(\cdot)$ denote the unknown smooth function with $f_i(0) = 0$. τ_i is the unknown constant delay, and τ_m is the upper bound of τ_i.

Control Objective: To design an adaptive control method while ensuring that all signals of the closed-loop system are bounded.

In order to make the structure of the controller simple and the calculation small, this paper uses MTNs to approximate the control signal and unknown functions. The approximation theorem of MTN has been given in our recent work [19].

3 Nonlinear Observer Design

The state variables cannot be measured directly in many practical systems. Therefore, it is necessary to develop an effective control scheme for nonlinear systems with unavailable states. In this paper, a MTN-based observer is designed to estimate the unmeasured states:

$$\dot{\hat{x}}_i = \hat{x}_{i+1} + l_i(y - \hat{x}_1) \qquad i = 1, \cdots, n \quad (2)$$

where $\hat{x}_{n+1} = u$. Let $\tilde{x} = x - \hat{x}$, be the observer error.

$$\dot{\tilde{x}}(t) = A\tilde{x}(t) + f(\bar{x}(t)) + h(\bar{x}(t-\tau))$$

where

$$A = \begin{bmatrix} -l_1 & & & \\ \vdots & l_{n-1} & & \\ -l_n & 0 & \cdots & 0 \end{bmatrix}$$

$$f(\bar{x}(t)) = [f_1(x_1(t)) \cdots f_n(x_n(t))]^{\mathrm{T}}$$

$$h(\bar{x}(t-\tau)) = [h_1(\bar{x}_1(t-\tau_1)) \cdots h_n(\bar{x}_n(t-\tau_n))]^{\mathrm{T}}$$

where A is a strict Hurwitz matrix and there is a matrix $P > 0$ satisfying that $A^{\mathrm{T}}P + PA = -I$.

Then the system (1) can be expressed as:

$$\begin{cases} \dot{y}(t) = \hat{x}_2 + \tilde{x}_2 + f_1(y(t)) + h_1(y(t-\tau_1)) \\ \dot{\hat{x}}_2(t) = \hat{x}_3(t) + l_2\tilde{x}_1(t) \\ \quad \vdots \\ \dot{\hat{x}}_n(t) = u + l_n\tilde{x}_1(t) \end{cases} \quad (3)$$

The backstepping design is carried out on the basis of the following coordinate transformation.

$$z_1 = y, z_i = \hat{x}_i - \alpha_{i-1}, i = 2, \cdots, n$$

Then, we have

$$\begin{cases} \dot{z}_1 = \hat{x}_2 + \tilde{x}_2 + f_1(y(t)) + h_1(y(t-\tau_1)) \\ \dot{z}_i = \hat{x}_{i+1}(t) + l_i\tilde{x}_1(t) - \dot{\alpha}_{i-1} \qquad i = 2, 3, \cdots, n \end{cases}$$

For the controller design, consider the following assumptions.

Assumption 1 [19]*:* For $1 \le i \le n$, there exists positive unknown smooth functions $\varpi_{il}(\bar{z}_l + \bar{\alpha}_{l-1})$ such that

$$|h_i(\bar{x}_i)| \le \sum_{l=1}^{i} |z_l| \varpi_{il}(\bar{z}_l + \bar{\alpha}_{l-1}) \quad (4)$$

where $\bar{z}_l = [z_1, \cdots, z_l]^{\mathrm{T}}$ and $\bar{\alpha}_{l-1} = [\alpha_1 \cdots \alpha_{l-1}]^{\mathrm{T}}$ with $\alpha_1 = 0$.

Assumption 2: To facilitate the later calculations, let us define a constant

$$\eta = \max\{N_i \|\theta_i^*\|^2 : i = 0, 1, 2, \cdots, n\}$$

where η is an unknown constant, N_i are the dimension of z_i, θ^* is the ideal constant weight vector in the MTN, and we define $\hat{\eta}$ as the estimate of η.

4 Stability Analysis

Theorem 1: Consider the nonlinear time-delay system (1). If choose the virtual control signals as

$$\alpha_i = -k_i z_i - \frac{1}{2\zeta_i^2} z_i \hat{\eta}, \ \ i = 1, \cdots, n-1 \quad (5)$$

the actual control signal as

$$u = -k_n z_n - \frac{1}{2\zeta_n^2} z_n \hat{\eta} \quad (6)$$

together with the adaptive laws defined as

$$\dot{\hat{\theta}}_i = \sum_{i=1}^{n} \frac{r}{2\zeta_i^2} z_i^2 - k_0 \hat{\eta} \quad (7)$$

then all the signals in the closed-loop system can be guaranteed to be bounded and tracking error enters inside the area $\Omega(\varepsilon)$.

Proof. Step 1: Consider the following Lyapunov function:

$$V_1 = \lambda \tilde{x}^{\mathrm{T}} P \tilde{x} + \frac{1}{2} z_1^2 + \frac{1}{2r} \tilde{\eta}^2 + \frac{1}{2c_2^2} \int_{t-\tau_1}^{t} z_1^2(\tau) \varpi_{l1}^2(z_1(\tau)) d\tau$$
$$+ \frac{\lambda^2}{2} \sum_{i=1}^{n} \sum_{l=1}^{i} \int_{t-\tau_i}^{t} z_l^2(\tau) \varpi_{il}^2 \left(\bar{z}_l(\tau) + \bar{\alpha}_{l-1}(\tau)\right) d\tau$$

where $\lambda > 0$ and $\tilde{\eta} = \eta - \hat{\eta}$.

The time derivative of V_1 is

$$
\begin{aligned}
\dot{V}_1 &= -\lambda\|\tilde{x}\|^2 + 2\lambda\tilde{x}^{\mathrm{T}}P(f+h) - \frac{1}{r}\tilde{\eta}\dot{\hat{\eta}} \\
&+ z_1\left(\hat{x}_2 + \tilde{x}_2 + f_1(z_1) + h_1(z_1(t-\tau_1))\right) \\
&- \frac{1}{2c_2^2} z_1^2(t-\tau_1)\varpi_{l1}^2(z_1(t-\tau_1)) \\
&+ \frac{1}{2c_2^2} z_1^2\varpi_{l1}^2(z_1) + \frac{\lambda^2}{2}\sum_{i=1}^{n}\sum_{l=1}^{i} z_l^2\varpi_{il}^2(\bar{z}_l + \bar{\alpha}_{l-1}) \\
&- \frac{\lambda^2}{2}\sum_{i=1}^{n}\sum_{l=1}^{i} z_l^2(t-\tau_i)\varpi_{il}^2\left(\bar{z}_l(t-\tau_i) + \bar{\alpha}_{l-1}(t-\tau_i)\right)
\end{aligned} \tag{8}
$$

where $f \triangleq (f_1(\bar{x}),\cdots,f_n(\bar{x}))^{\mathrm{T}}$. Then, approaching unknown function with MTN, for any given $\varepsilon_0 > 0$, there exists MTN $\boldsymbol{\theta}_0^{*\mathrm{T}}\boldsymbol{S}_0(X_0)$, such that

$$
f(X_0) = \boldsymbol{\theta}_0^{*\mathrm{T}}\boldsymbol{S}_0(X_0) + \delta_0(X_0), \|\delta_0(X_0)\| \le \varepsilon_0 .
$$

As $S_0^{\mathrm{T}}S_0 \le N_0$, N_0 is the dimension of S_0 and according to the definition of η, we have

$$
2\lambda\tilde{x}^{\mathrm{T}}Pf \le 2\|\tilde{x}\|^2 + \lambda^2\|p\|^2\eta + \lambda^2\|p\|^2\varepsilon_0^2 \tag{9}
$$

According to Assumption 1, we have

$$
\begin{aligned}
&2\lambda\tilde{x}^{\mathrm{T}}Ph \le 2n(n+1)\|\tilde{x}\|^2\|P\|^2 \\
&+\frac{\lambda^2}{2}\sum_{i=1}^{n}\sum_{l=1}^{i} z_l^2(t-\tau_i)\varpi_{il}^2\left(\bar{z}_l(t-\tau_i) + \bar{\alpha}_{l-1}(t-\tau_i)\right) \\
&z_1\tilde{x}_2 \le \frac{1}{2}c_1^2 z_1^2 + \frac{1}{2c_1^2}\|\tilde{x}\|^2
\end{aligned} \tag{10}
$$

Substituting (9) and (10) into (8), we have

$$
\begin{aligned}
\dot{V}_1 &= -\Pi\|\tilde{x}\|^2 + z_1\left(\hat{x}_2 + \tilde{f}_1\right) - \frac{1}{r}\tilde{\eta}\dot{\hat{\eta}} - \frac{1}{2}z_1^2 \\
&+ \frac{\lambda^2}{2}\sum_{i=2}^{n}\sum_{l=2}^{i} z_l^2\varpi_{il}^2(\bar{z}_l + \bar{\alpha}_{l-1}) + \lambda^2\|p\|^2\eta + \lambda^2\|p\|^2\varepsilon_0^2
\end{aligned}
$$

where $\Pi = \lambda - 2 - 2n(n+1)\|P\|^2 - \frac{1}{2c_1^2}$ and

$$
\tilde{f}_1(\mathrm{X}_1) = \tilde{f}_1(\mathrm{z}_1) + \frac{1}{2}\left(\sum_{i=1}^{2} c_i^2 + \lambda^2 z_1^2\varpi_{11}^2 + \frac{1}{c_2^2}z_1\varpi_{l1}^2(z_1) + 1\right)z_1 .
$$

Next, take the intermediate control signal $\hat{\alpha}_1(X_1)$ as $\hat{\alpha}_1(X_1) = \tilde{f}_1$, where $k_1 > 0$. However, $\hat{\alpha}_1(X_1)$ is an unknown nonlinear function as it contains $f_1(z_1)$, which cannot be implemented in practice. Therefore, we use MTN $\boldsymbol{\theta}_1^{*\mathrm{T}}\boldsymbol{S}_1(X_1)$ approaching it, such that

$$
\hat{\alpha}_1(X_1) = \theta_1^{*\mathrm{T}}S_1(X_1) + \delta_1(X_1), |\delta_1(X_1)| \le \varepsilon_1
$$

From the definition of η, we have

$$
z_1\hat{\alpha}_1 \le \frac{1}{2\zeta_1^2}z_1^2\eta + \frac{1}{2}\zeta_1^2 + \frac{1}{2}z_1^2 + \frac{1}{2}\varepsilon_1^2 . \tag{11}
$$

And by the definition of α_1 and $\hat{x}_2 = z_2 + \alpha_1$, we have

$$
\begin{aligned}
\dot{V}_1 &\le -\Pi\|\tilde{x}\|^2 + z_1 z_2 - k_1 z_1^2 + b_1 \\
&+ \frac{1}{r}\tilde{\eta}\left(\frac{r}{2\zeta_1^2}z_1^2 - \dot{\hat{\eta}}\right) + \frac{\lambda^2}{2}\sum_{i=2}^{n}\sum_{l=2}^{i} z_l^2\varpi_{il}^2(\bar{z}_l + \bar{\alpha}_{lf})
\end{aligned}
$$

where

$$
b_1 = \lambda^2\|p\|^2\eta + \lambda^2\|p\|^2\varepsilon_0^2 + \frac{1}{2}\zeta_1^2 + \frac{1}{2}\varepsilon_1^2 .
$$

Step m: $(2 \le m \le n-1)$. Consider the following Lyapunov function:

$$
V_m = V_{m-1} + \frac{1}{2}z_m^2 .
$$

Similarly to step 1, we have

$$
\begin{aligned}
\dot{V}_m &\le -\Pi\|\tilde{x}\|^2 + \sum_{i=1}^{m-1} z_i z_{i+1} - \sum_{i=1}^{m} k_i z_i^2 + b_{m-1} \\
&+ \frac{1}{r}\tilde{\eta}\left(\sum_{i=1}^{m-1}\frac{r}{2\zeta_i^2}z_i^2 - \dot{\hat{\eta}}\right) + z_m(\hat{x}_{m+1} - \hat{\alpha}_m) \\
&+ \frac{\lambda^2}{2}\sum_{i=m+1}^{n}\sum_{l=m+1}^{i} z_l^2\varpi_{il}^2(\bar{z}_l + \bar{\alpha}_{l-1}) - \frac{1}{2}z_m^2
\end{aligned} \tag{12}
$$

where

$$
\tilde{f}_m(X_m) = l_m\tilde{x}_1 - \dot{\alpha}_{m-1} + z_m\left(\frac{1}{2} + \frac{\lambda^2}{2}\sum_{i=m}^{n}\varpi_{lm}^2(\bar{z}_m + \bar{\alpha}_{m-1})\right).
$$

Then, take the intermediate control signal $\hat{\alpha}_m(X_m) = \tilde{f}_m$, and we can obtain

$$
-z_m\hat{\alpha}_m \le \frac{1}{2a_m^2}z_m^2\eta + \frac{1}{2}\zeta_m^2 + \frac{1}{2}z_m^2 + \frac{1}{2}\varepsilon_m^2 . \tag{13}
$$

Then, it implies

$$
\begin{aligned}
\dot{V}_m &\le -\Pi\|\tilde{x}\|^2 + \sum_{i=1}^{m} z_i z_{i+1} + \frac{1}{r}\tilde{\eta}\left(\sum_{i=1}^{m}\frac{r}{2\zeta_i^2}z_i^2 - \dot{\hat{\eta}}\right) \\
&- \sum_{i=1}^{m} k_i z_i^2 + \frac{\lambda^2}{2}\sum_{i=m+1}^{n}\sum_{l=m+1}^{i} z_l^2\varpi_{il}^2(\bar{z}_l + \bar{\alpha}_{l-1}) + b_m
\end{aligned}
$$

where

$$
b_m = \lambda^2\|p\|^2\eta + \lambda^2\|p\|^2\varepsilon_0^2 + \frac{1}{2}\sum_{i=1}^{m}\zeta_i^2 + \frac{1}{2}\sum_{i=1}^{m}\varepsilon_i^2 .
$$

Step n: Consider the following Lyapunov function:

$$
V_n = V_{n-1} + \frac{1}{2}z_n^2 .
$$

Following a similar procedure and by the definition of u and $\dot{\hat{\theta}}$, we have

$$
\dot{V}_n \le -\Pi\|\tilde{x}\|^2 + \sum_{i=1}^{n-1} z_i z_{i+1} - \sum_{i=1}^{n} k_i z_i^2 + b_n + \frac{k_0}{r}\tilde{\eta}\hat{\eta} \tag{14}
$$

where

$$
b_n = \lambda^2\|p\|^2\eta + \lambda^2\|p\|^2\varepsilon_0^2 + \frac{1}{2}\sum_{i=1}^{n}\zeta_i^2 + \frac{1}{2}\sum_{i=1}^{n}\varepsilon_i^2 .
$$

Then, we have

$$
\begin{aligned}
z_i z_{i+1} &\le \frac{1}{2}z_i^2 + \frac{1}{2}z_{i+1}^2 \\
\tilde{\eta}\hat{\eta} &= \tilde{\eta}(\eta - \tilde{\eta}) \le -\frac{1}{2}\tilde{\eta}^2 + \frac{1}{2}\eta^2
\end{aligned} \tag{15}
$$

Substituting (15) into (14), we have

$$
\begin{aligned}
\dot{V}_n &\le -\Pi\|\tilde{x}\|^2 - \sum_{i=1}^{n}(k_i - \frac{3}{2})z_i^2 - \frac{k_0}{2r}\tilde{\eta}^2 + \bar{b}_n \\
\bar{b}_n &= b_n + \frac{k_0}{2r}\eta^2 + \frac{1}{4\pi^2}
\end{aligned}
$$

And denote

$$a = \min\left\{ \frac{\Pi}{\lambda}, 2(k_i - \frac{3}{2}), k_0 \middle| i = 1, \cdots, n \right\}.$$

Then, there exists a positive constant $\bar{a}$ such that

$$\dot{V}_n \le -\bar{a} V_n + \bar{b}_n \quad (16)$$

It can be concluded that all the signals in the closed-loop system are bounded in $\Omega(\varepsilon)$, which are the desired results and the proof is completed.

Remark 1: According to (16), one has

$$\frac{d(E[V])}{dt} = E[V] \le -\bar{a} E[V] + \bar{b}$$

where $E[V]$ denotes the expectation of V.

Then, inequality (16) implies that

$$0 \le E[V(t)] \le V(0) e^{-\bar{a}t} + \frac{\bar{b}}{\bar{a}}, \forall t \ge 0$$

Therefore, we can conclude that the tracking error converges to a small residual set around the origin in the sense of mean quartic value, we can properly adjust the parameters $\bar{a}$ and $\bar{b}$.

5 Simulation Results

In this section, a numerical simulation example is presented to demonstrate the effectiveness of the proposed control method.

Example: Consider the following nonlinear time-delay system

$$\begin{cases} \dot{x}_1 = x_2 + x_1 \sin(x_1) + 0.5 x_1^3 (t - \tau_1) \\ \dot{x}_2 = x_3 + x_2 \sin(\frac{0.2}{1 + x_1^2}) + x_1(t - \tau_2) x_2^2 (t - \tau_2) \\ \dot{x}_3 = u + x_1 x_3^2 e^{-x_2} + 0.5 x_3^2 (t - \tau_3) \\ y = x_1 \end{cases} \quad (17)$$

where the initial states are chosen as $x_1 = 0.01$, $x_2 = 0.01$, and $x_3 = 0.01$, the given reference signal $y_d = 0.5\sin(t)$, and the observer is designed as

$$\dot{\hat{x}}_i = \hat{x}_{i+1} + l_i (y - \hat{x}_1) \quad i = 1, 2$$

$$\dot{\hat{x}}_3 = u + l_3 (y - \hat{x}_1)$$

According to Theorem 1, the virtual control function $\alpha_i (i = 1, 2)$ and the true control law u are chosen respectively as

$$\alpha_i = -k_i z_i - \frac{1}{2\zeta_i^2} z_i \hat{\eta}, \quad i = 1, 2$$

$$u = -k_3 z_3 - \frac{1}{2\zeta_3^2} z_3 \hat{\eta}$$

where $z_1 = y - y_d$, $z_i = \hat{x}_i - \alpha_{i-1} (i = 2, 3)$. The adaptive law is given as

$$\dot{\hat{\theta}}_i = \sum_{i=1}^{n} \frac{r}{2\zeta_i^2} z_i^2 - k_0 \hat{\eta}.$$

In the simulation, the time delays are chosen as $\tau_1 = \tau_2 = \tau_3 = 0.5$, therefore the upper bound of time delays is chosen as $\tau_m = 0.5$, and the design parameters are chosen as $l_1 = l_2 = l_3 = 50$, $k_0 = 10$, $k_1 = 16$, $k_2 = 2$, $k_3 = 8$, $\zeta_1 = 6, \zeta_2 = 4, \zeta_3 = 8$. The simulation results are illustrated by Fig. 1-4, respectively. Fig. 1 shows the system output y and reference signal y_d. Fig. 2 describes the tracking error $y - y_d$, which shows that the proposed controller achieves good tracking performance. Fig. 3 depicts the trajectory of the control signal u. Fig. 4 displays the state variables x_2 and x_3 are bounded. The presented simulation results illustrate the effectiveness of the adaptive MTN control shame proposed in this paper.

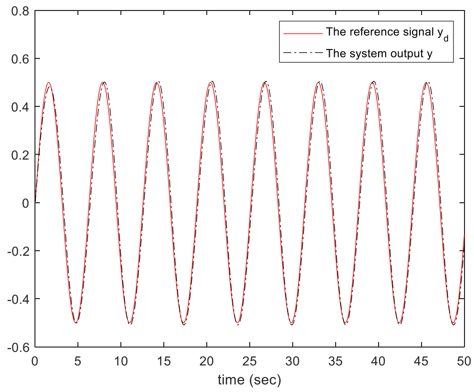

Fig. 1: System output y and reference signal y_d.

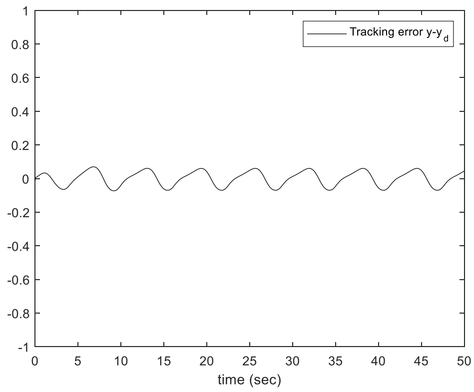

Fig. 2: The tracking error $y - y_d$.

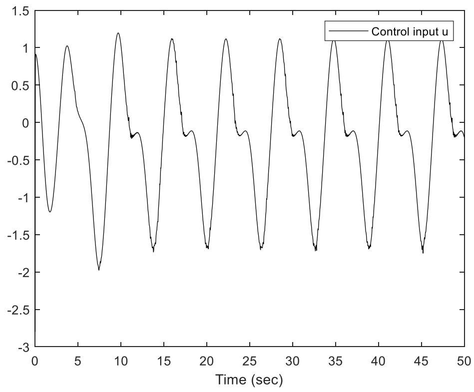

Fig. 3: The trajectory of control signal u.

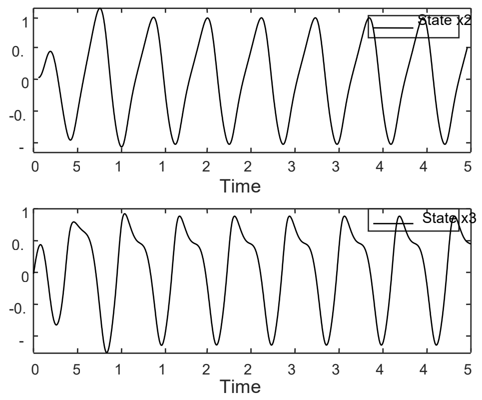

Fig. 4: The state variables x_2 and x_3.

6 Conclusions

In this paper, the problem of adaptive MTN tracking control for a class of nonlinear strict feedback systems with unknown time-delay is studied. A direct adaptive MTN control scheme is proposed by using the backstepping method. In addition, the observer is designed to estimate the unknown state effectively. It is proved that all the signals in the closed-loop system are bounded, and the output signal can track the track of the reference signal with a small error. Finally, the simulation results verify the effectiveness of the method. Furthermore, the proposed method can also be used to solve switching systems and MIMO systems with time-delay.

References

[1] Kanellakopoulos, I., Kokotovic, P. and Morse, A., Systematic design of adaptive controllers for feedback linearizable systems. IEEE Transactions on Automatic Control, 1991. 11(26): p. 1241-1253.

[2] Wang H., Tanaka K., and Griffin M., An approach to fuzzy control of nonlinear systems: stability and design issues. IEEE Transactions on Fuzzy Systems, 2002. 4(1): p.14-23.

[3] Yu, J., Shi, P. and Zhao, L., Finite-time command filtered backstepping control for a class of nonlinear systems. Automatica, 2018. 92: p. 173-180.

[4] Furuta, K., Sliding mode control of a discrete system. System and Control Letters, 1990. 14(2): p. 145-152.

[5] Zhang T., Adaptive neural network control for strict-feedback nonlinear systems using backstepping design. Automatica, 2000. 36(12): p. 1835-1846.

[6] Qi, R., Tao, G., Jiang, B. and Tan C., Adaptive control schemes for discrete-time T–S fuzzy systems with unknown parameters and actuator failures. IEEE Transactions on Fuzzy Systems, 2012. 20(3): p. 471-486.

[7] Hao, L. and Lin, W., Universal adaptive control of nonlinear systems with unknown growth rate by output feedback. Automatica, 2006. 42(10): p. 1783-1789.

[8] Zhou, Q., Shi, P., Lu, J. and Xu, S., Adaptive output-feedback fuzzy tracking control for a class of nonlinear systems. IEEE Transactions on Fuzzy Systems, 2011. 19(5): p. 972-982.

[9] Lee, H., Robust adaptive fuzzy control by backstepping for a class of MIMO nonlinear systems. IEEE Transactions on Fuzzy Systems, 2011. 19(2): p. 265-275.

[10] Yang, Y. and Zhou, C., Robust adaptive fuzzy tracking control for a class of perturbed strict-feedback nonlinear systems via small-gain approach. Information Sciences, 2005. 170(2-4): p. 211-234.

[11] Chiang, M. and Fu, L., Adaptive stabilization of a class of uncertain switched nonlinear systems with backstepping control. Automatica, 2014. 50(8): p. 2128-2135.

[12] Tong, S., Huo, B. and Li, Y., Observer-based adaptive decentralized fuzzy fault-tolerant control of nonlinear large-scale systems with actuator failures. IEEE Transactions on Fuzzy Systems, 2014. 22(1): p. 1-15.

[13] Li, H. and Tong, S., A hybrid adaptive fuzzy control for a class of nonlinear MIMO systems. IEEE Transactions on Fuzzy Systems, 2003. 11(1): p. 24-34.

[14] Han, Y. and Yan, H., Multi-dimensional Taylor network(MTN)-based adaptive tracking control for a class of nonlinear systems with input constraints. In 37th China Control Conference. 2018: p. 802-807.

[15] Yan, H., Sun, Q. and Zhou, B., Multidimensional Taylor network optimal control of SISO nonlinear systems for tracking by output feedback. Optimal Control Applications and Methods, 2018. 39(2): p. 919-932.

[16] Kang, A. and Yan, H., Asymptotically tracking and dynamic regulation of SISO nonlinear system based on multi-dimensional Taylor network controller. In 15th International Conference on Control, Automation and Systems, Busan, Korea, 2015. p. 903-908.

[17] Zhang, C. and Yan, H., Multidimensional Taylor network adaptive control for MIMO time-varying uncertain nonlinear systems with noises. International Journal of Robust and Nonlinear Control, 2019. 30(1): p. 397-420.

[18] Han, Y. and Yan, H., A multi-dimensional Taylor network (MTN)-based approach for nonlinear stochastic systems tracking control. In 15th International Conference on Control, Automation and Systems, 2015. p. 892-896.

[19] Han, Y., Output-feedback adaptive tracking control of stochastic nonlinear systems using multi-dimensional Taylor network. International Journal of Adaptive Control and Signal Processing, 2018. 32(3): p. 494-510.

[20] Han, Y. and Yan, H., Observer-based multi-dimensional Taylor network decentralised adaptive tracking control of large-scale stochastic nonlinear systems. International Journal of Control, 2018: p. 1-14.

[21] Zhou, Q., Shi, P., Lu, J. and Xu, S., Observer-based adaptive neural network control for nonlinear stochastic systems with time delay. IEEE Transactions on Neural Networks and Learning Systems, 2013. 24(1): p. 71-80.

[22] Wang, H., Chen, B. and Lin, C., Adaptive neural control for strict-feedback stochastic nonlinear systems with time-delay. Neurocomputing, 2012. 77(1): p. 267-274.

[23] Chen, W., Jiao, L., Li, J., Li, R., Adaptive NN backstepping output-Feedback control for stochastic nonlinear strict-feedback systems with time-varying delays. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), 2010. 40(3): p. 939-950.

[24] Gu, Y. and Ding, F., Parameter estimation for an input nonlinear state space system with time delay. Journal of the Franklin Institute, 2014. 351(12): p. 5326-5339.