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时变时滞非线性系统的自适应神经网络控制

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摘要: 对于一类具有未知时变时滞和虚拟控制系数的不确定严格反馈非线性系统, 基于后推设计提出一种自适应神经网络控制方案. 选取适当的 Lyapunov-Krasovskii 泛函补偿未知时变时滞不确定项. 通过构造连续的待逼近函数来解决利用神经网络对未知非线性函数进行逼近时出现的奇异问题. 通过引入一个新的中间变量, 保证了虚拟控制求导的正确性. 仿真算例表明, 所设计的控制器能保证闭环系统所有信号是半全局一致终结有界的, 且跟踪误差收敛到零的一个邻域内.

关键词: 严格反馈非线性系统; 后推; 自适应控制; 神经网络控制; 时变时滞

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Adaptive neural network control of nonlinear time-varying delay systems

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Abstract: Based on backstepping, an adaptive neural network control scheme is proposed for a class of perturbed strict-feedback nonlinear systems with unknown time-varying delays and virtual control coefficients. By choosing appropriate Lyapunov-Krasovskii functionals, the unknown time-varying delay uncertainties can be compensated for. The continuous approximation functions are constructed to solve the singularity problem which occurs when neural networks are used to approximate the unknown nonlinear functions. By introducing a new intermediate variable, the derivative of virtual control is guaranteed to be right. Simulation results show that the proposed controller can guarantee that all the signals in the closed-loop system are semi-global uniformly ultimately bounded, and the tracking error converges to a neighborhood of zero.

Key words: strict-feedback nonlinear systems; backstepping; adaptive control; neural network control; time-varying delay

1 引言

近年来, 基于神经网络或模糊系统的通用逼近性, 对不确定非线性动态系统自适应控制的研究取得了大量成果^[1-6]. 对于一类非线性规范型系统, 文献[1-3]提出了自适应神经网络或模糊控制方案; [4-6]将规范型系统扩展到一类控制输入具有特殊三角结构的 MIMO 非线性系统中, 对这一类系统提出了不同的神经网络跟踪控制方案; 对于具有三角结构的一类参数化严格反馈非线性系统, [7]提出了一种称为后推的系统设计方法.

时滞是许多工程系统固有的特性, 它的存在会降低系统的控制性能, 甚至破坏系统的稳定性^[8], 因此

对它的研究就显得尤为重要. 时滞系统的稳定性分析中, 两个主要的工具是 Lyapunov-Krasovskii (L-K)^[9]和 Lyapunov-Razumikhin 泛函^[10]. 利用文献[9]中的 L-K 泛函来补偿未知时滞不确定项, 提出了一些自适应控制方案^[5-6, 11-16], 但文献[11]中神经网络只用来逼近无时滞的非线性函数, 而且假设系统时滞函数被已知上界函数所界定. 对于一类具有死区的 MIMO 时变时滞非线性系统, 文献[5]提出了一种自适应控制方案. 在利用神经网络对未知非线性函数进行逼近时, 由于构造的待逼近函数在误差为零处不连续, 不能直接用神经网络进行逼近, [5, 11]在误差为零的邻域内及邻域外分别设计控制律, 解决了

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利用神经网络对未知非线性函数逼近出现的奇异问题,但这也导致所设计的控制器不再连续.[12,14]针对一类严格反馈常时滞非线性系统,提出了自适应控制方案.在处理利用神经网络对未知函数逼近时出现的奇异问题时,同样在误差为零的邻域内及邻域外分别设计控制律,通过设计一个有界且可导的函数乘到控制器上,设计出连续且可导的控制器,但所设计的可导函数相当复杂,而且证明过程也比较繁琐.对于一类严格反馈时滞系统,利用双曲正切函数的性质,构造出连续的待逼近函数,提出了连续自适应控制方案^[13,16]. [6]针对一类具有未知时变时滞及死区的MIMO非线性系统,通过引入max函数构造出连续的逼近函数,提出了一种连续的神经网络跟踪控制方案.[11-12,14]对一类具有时滞不确定的严格反馈非线性系统,利用L-K方法提出几种自适应控制方案.存在的不足之处是:在文献[11-12,14]中,利用复合函数求导规则对虚拟控制 α_{i-1} 求导时均未对虚拟控制中的 $k_{i-1}(t)$ 求偏导.由于 $k_{i-1}(t)$ 中含有时变时滞状态,这将导致对虚拟控制的求导在数学上是可疑的^[11-12,14].若直接对 $k_{i-1}(t)$ 求导则会出现循环求导问题,从而使得求导过程非常复杂且无法实现.[14,16]利用模糊系统逼近未知函数时所确定的建模变量值得商榷.

本文针对一类具有未知时变时滞和虚拟控制系数的不确定严格反馈非线性系统,利用L-K泛函和后推设计方法,提出一种自适应神经网络跟踪控制方案.类似文献[6],通过构造连续的待逼近函数,解决了利用神经网络逼近未知非线性函数时出现的奇异问题;针对[11-12,14]中利用复合函数求导规则对虚拟控制求导时缺少对包含时滞项的时变增益求导的数学问题,通过巧妙地引入一个新的中间变量,保证了虚拟控制求导的正确性;利用[15]中的方法,使用神经网络权向量的加权范数来代替直接使用权向量作为估计的参数,大大减少了自适应参数的调节个数;[12-16]讨论了一类常时滞问题,本文将常时滞推广到更一般的时变时滞系统,进一步结合Young's不等式,放宽了对时滞项假设的限制.

2 问题的描述及基本假设

考虑如下—类具有时变时滞及扰动的SISO非线性系统:

$$\begin{cases} \dot{x}_i = f_i(\bar{x}_i) + g_i(\bar{x}_i)x_{i+1} + h_i(\bar{x}_{\tau_i}) + d_i(t, x), \\ \dot{x}_n = f_n(x) + g_n(x)u + h_n(\bar{x}_{\tau_n}) + d_n(t, x), \\ y = x_1. \end{cases} \quad (1)$$

其中: $1 \leq i \leq n-1$; $x = [x_1, x_2, \dots, x_n]^T \in R^n$ 为系统的状态向量; $\bar{x}_i = [x_1, x_2, \dots, x_i]^T (i = 1, 2, \dots, n-$

1); $u \in R$ 和 $y \in R$ 分别为系统的输入和输出;

$$\begin{aligned} \bar{x}_{\tau_i} &= [x_{\tau_1}, x_{\tau_2}, \dots, x_{\tau_i}]^T = \\ &[x_1(t - \tau_1(t)), x_2(t - \tau_2(t)), \dots, x_i(t - \tau_i(t))]^T, \\ &i = 1, 2, \dots, n \end{aligned}$$

为时滞状态向量,这里 $\tau_i(t)$ 为未知的状态时变时滞; $f_i(\cdot), g_i(\cdot), h_i(\cdot)$ 为未知连续函数; $d_i(\cdot)$ 为外来干扰.当 $t \in [-\tau_{\max}, 0]$ 时, $x(t) = \omega(t)$, $\omega(t)$ 为已知的初始状态向量函数,正常数 τ_{\max} 的定义将在稍后的假设中给出.

控制目标是为系统(1)设计一个自适应控制输入 u ,使得系统的输出 y 跟随指定的期望轨迹 y_d ,且保证闭环系统中的所有信号有界.参考轨迹向量为 $\bar{y}_{di} = [y_d, y_d^{(1)}, \dots, y_d^{(i)}]^T (i = 1, 2, \dots, n)$.

假设 1 期望的轨迹向量 \bar{y}_{di} 是连续已知的,满足 $\bar{y}_{di} \in \Omega_{di} \subset R^{i+1} (i = 1, 2, \dots, n)$,其中 Ω_{di} 为已知紧集.

假设 2 时变时滞不确定项满足

$$\begin{aligned} |h_i(\bar{x}_{\tau_i})| &\leq \theta_i \sum_{j=1}^i \rho_{i,j}(x_j(t - \tau_j(t))), \\ &i = 1, 2, \dots, n. \end{aligned}$$

其中: θ_i 为未知正常数,而 $\rho_{i,j}(x_j(t))$ 为已知正的连续函数.

假设 3 未知状态时变时滞满足 $0 \leq \tau_i(t) \leq \tau_{\max}$, $\dot{\tau}_i(t) \leq \bar{\tau}_{\max} < 1 (i = 1, 2, \dots, n)$,其中 τ_{\max} 和 $\bar{\tau}_{\max}$ 是已知正常数.

假设 4 $g_i(\bar{x}_i) (i = 1, 2, \dots, n)$ 是未知的,存在未知的正常数 b_m 和 b_M 使得 $0 < b_m \leq |g_i(\bar{x}_i)| \leq b_M < \infty$.不失一般性,这里假设 $g_i(\bar{x}_i) \geq b_m > 0 (i = 1, 2, \dots, n)$.

假设 5 对于 $i = 1, 2, \dots, n$,存在未知光滑正函数 $m_i(\bar{x}_i)$ 使 $|d_i(t, x)| \leq m_i(\bar{x}_i)$ 成立.

本文中 $\|\cdot\|$ 表示向量的2-范数,即欧氏范数, $(\cdot)^* = (\hat{\cdot})$.

3 自适应控制器的设计

为了利用后推设计自适应控制器,有如下坐标变换: $e_1 = x_1 - y_d, e_2 = x_2 - \alpha_1, \dots, e_n = x_n - \alpha_{n-1}$,其中 $\alpha_i (i = 1, 2, \dots, n-1)$ 表示稍后确定的虚拟控制.

假设 Ω_{Z_i} 为一个紧集, $W_i^{*T} S_i(Z_i)$ 为一个径向基函数网络在 Ω_{Z_i} 上对未知连续函数 $\varphi_i(Z_i)$ 的一个逼近,其中 $\varphi_i(Z_i)$ 和变量 Z_i 将稍后给出.于是有

$$\varphi_i(Z_i) = W_i^{*T} S_i(Z_i) + \delta_i(Z_i), \quad (2)$$

其中

$$S_i(Z_i) = [s_{i1}(Z_i), \dots, s_{il_i}(Z_i)]^T \in R^{l_i},$$

$$s_{ij}(Z_i) = \exp \left[- \frac{(Z_i - \mu_{ij})^T (Z_i - \mu_{ij})}{\phi_{ij}^2} \right], \quad (3)$$

$j = 1, 2, \dots, l, i = 1, 2, \dots, n, \mu_{ij} = [\mu_{ij1}, \mu_{ij2}, \dots, \mu_{ijq_{ij}}]^T, \mu_{ij}$ 和 ϕ_{ij} 分别表示高斯函数的中心和宽度; W_i^* 表示未知理想的权向量, 通常定义为

$$W_i^* = \arg \min_{W_i \in R^l} \left[\sup_{Z_i \in \Omega_{Z_i}} |W_i^T S_i(Z_i) - \varphi_i(Z_i)| \right];$$

而逼近误差 $\delta_i(Z_i)$ 满足 $|\delta_i(Z_i)| \leq \varepsilon_i, \forall Z_i \in \Omega_{Z_i}, \varepsilon_i > 0$ 为未知常数.

为了减少自适应参数的调节个数, 定义新的未知常数 $\lambda_i^* = b_m^{-1} \|W_i^*\|^2 (i = 1, 2, \dots, n)$. 本文利用李亚普诺夫方法直接估计 λ_i^* 来代替估计理想的网络权向量 W_i^* , 从而使得在后推设计的每一步中, 只需调节一个参数. 神经网络控制律及自适应律选择如下:

$$\alpha_i = - \frac{\hat{\lambda}_i}{2\eta_i^2} \|S_i(Z_i)\|^2 e_i - k_i(t) e_i, \quad (4)$$

$$\dot{\hat{\lambda}}_i = \frac{\gamma_i}{2\eta_i^2} \|S_i(Z_i)\|^2 e_i^2 - \sigma_i \hat{\lambda}_i. \quad (5)$$

其中: $\gamma_i, \sigma_i, \eta_i$ 为正的设计常数; $\hat{\lambda}_i$ 为未知参数 λ_i^* 的估计, 估计误差 $\tilde{\lambda}_i = \lambda_i^* - \hat{\lambda}_i; k_i(t) = k_{i1} + k_{i2}(t)$. 这里

$$k_{i2}(t) = \frac{k_{i3}}{\beta_i} \sum_{j=1}^i \sum_{k=1}^j \int_{t-\tau_{\max}}^t \rho_{j,k}^2(x_k(\tau)) d\tau, \quad (6)$$

而 $k_{i1} > 3/(2b_m), k_{i3} > 0; \beta_i = 2(1 - \bar{\tau}_{\max})(e_i^2 + c_i^2), c_i$ 为很小的常数.

注 1 由式(5)可知, 对于给定的初始条件 $\hat{\lambda}_i(t_0) \geq 0 (i = 1, 2, \dots, n)$. 可以得到, 当 $t \geq 0$ 时, $\hat{\lambda}_i(t)$ 都是非负的.

下面给出后推设计过程.

Step 1 ($i = 1$) 考虑第 1 个子系统的误差方程 $e_1 = x_1 - y_d$, 定义标量函数 $V_{e_1} = e_1^2/2$, 则有

$$\begin{aligned} \dot{V}_{e_1} = & e_1(f_1(x_1) + g_1(x_1)x_2 + h_1(x_{\tau_1}) + \\ & d_1(t, x) - \dot{y}_d). \end{aligned} \quad (7)$$

利用 Young's 不等式, 结合假设 2 和假设 5 可得

$$e_1 h_1(x_{\tau_1}) \leq |e_1| \theta_1 \rho_{11}(x_1(t - \tau_1(t))) \leq \frac{\theta_1^2 e_1^2}{2} + \frac{\rho_{11}^2(x_1(t - \tau_1(t)))}{2}, \quad (8)$$

$$e_1 d_1(t, x) \leq \frac{m_1^2(x_1) e_1^2}{2a_{11}^2} + \frac{a_{11}^2}{2}. \quad (9)$$

其中: $\rho_{11}(x_1(t - \tau_1(t)))$ 和 $m_1(x_1)$ 分别由假设 2 和假设 5 给出; a_{11} 为任意给定的正常数.

将式(8)和(9)代入(7)可得

$$\begin{aligned} \dot{V}_{e_1} \leq & e_1 \left(f_1(x_1) + g_1(x_1)x_2 + \frac{\theta_1^2 e_1}{2} + \frac{m_1^2(x_1) e_1}{2a_{11}^2} - \right. \\ & \left. \dot{y}_d \right) + \frac{\rho_{1,1}^2(x_1(t - \tau_1(t)))}{2} + \frac{a_{11}^2}{2}. \end{aligned} \quad (10)$$

为了消除式(10)中的时变时滞不确定项, 定义如

下 Lyapunov-kravskii 泛函:

$$V_{U_1} = \frac{1}{2(1 - \bar{\tau}_{\max})} \int_{t-\tau_1(t)}^t \rho_{1,1}^2(x_1(\tau)) d\tau.$$

对上式求导可得

$$\begin{aligned} \dot{V}_{U_1} = & \frac{1}{2(1 - \bar{\tau}_{\max})} \{ \rho_{1,1}^2(x_1(t)) - \\ & \rho_{1,1}^2(x_1(t - \tau_1(t)))(1 - \dot{\tau}_1(t)) \}. \end{aligned} \quad (11)$$

由式(10)和(11)可得

$$\begin{aligned} \dot{V}_{e_1} + \dot{V}_{U_1} \leq & e_1 \varphi_1(Z_1) + e_1 g_1(x_1)(e_2 + \alpha_1) + \\ & \frac{a_{11}^2}{2} + \frac{1}{2(1 - \bar{\tau}_{\max})} \left(1 - \frac{e_1^2}{c_1^2} \right) U_1. \end{aligned} \quad (12)$$

其中

$$\begin{aligned} U_1 = & \rho_{1,1}^2(x_1), \\ \varphi_1(Z_1) = & f_1(x_1) + \frac{\theta_1^2 e_1}{2} + \frac{m_1^2(x_1) e_1}{2a_{11}^2} + \\ & \frac{e_1}{2(1 - \bar{\tau}_{\max}) c_1^2} U_1 - \dot{y}_d. \end{aligned} \quad (13)$$

这里 $Z_1 = [x_1, y_d, \dot{y}_d]^T \in R^3$. 由式(2)可得

$$\begin{aligned} \dot{V}_{e_1} + \dot{V}_{U_1} \leq & W_1^{*T} S_1(Z_1) e_1 + \delta_1(Z_1) e_1 + e_1 g_1(x_1)(e_2 + \\ & \alpha_1) + \frac{a_{11}^2}{2} + \frac{1}{2(1 - \bar{\tau}_{\max})} \left(1 - \frac{e_1^2}{c_1^2} \right) U_1. \end{aligned} \quad (14)$$

选择如下 Lyapunov 函数:

$$V_1 = V_{e_1} + V_{U_1} + \frac{b_m}{2\gamma_1} \tilde{\lambda}_1^2. \quad (15)$$

由 Young's 不等式可知

$$W_1^{*T} S_1(Z_1) e_1 \leq \frac{b_m \lambda_1^*}{2\eta_1^2} S_1^T(Z_1) S_1(Z_1) e_1^2 + \frac{\eta_1^2}{2}.$$

对式(15)求导可得

$$\begin{aligned} \dot{V}_1 \leq & \frac{b_m \lambda_1^*}{2\eta_1^2} S_1^T(Z_1) S_1(Z_1) e_1^2 + \delta_1(Z_1) e_1 + \\ & e_1 g_1(x_1) \alpha_1 - \frac{b_m}{\gamma_1} \tilde{\lambda}_1 \dot{\hat{\lambda}}_1 + \frac{\eta_1^2}{2} + \frac{a_{11}^2}{2} + \\ & g_1(x_1) e_1 e_2 + \frac{1}{2(1 - \bar{\tau}_{\max})} \left(1 - \frac{e_1^2}{c_1^2} \right) U_1. \end{aligned} \quad (16)$$

由于 $g_1(x_1) \geq b_m > 0$, 结合式(4)可知

$$\begin{aligned} e_1 g_1(x_1) \alpha_1 = & - g_1(x_1) \left(k_1(t) e_1^2 + \frac{\hat{\lambda}_1}{2\eta_1^2} S_1^T(Z_1) S_1(Z_1) e_1^2 \right) \leq \\ & - b_m k_1(t) e_1^2 - \frac{b_m \hat{\lambda}_1}{2\eta_1^2} S_1^T(Z_1) S_1(Z_1) e_1^2. \end{aligned} \quad (17)$$

将式(17)和(5)代入(16)可得

$$\begin{aligned} \dot{V}_1 \leq & - b_m k_1(t) e_1^2 + \delta_1(Z_1) e_1 + \frac{\sigma_1 b_m \hat{\lambda}_1}{\gamma_1} \hat{\lambda}_1 + \frac{\eta_1^2}{2} + \\ & \frac{a_{11}^2}{2} + g_1(x_1) e_1 e_2 + \frac{1}{2(1 - \bar{\tau}_{\max})} \left(1 - \frac{e_1^2}{c_1^2} \right) U_1. \end{aligned}$$

利用不等式

$$\delta_1(Z_1) e_1 \leq e_1^2/2 + \varepsilon_1^2/2,$$

$$\frac{\sigma_1 b_m \tilde{\lambda}_1}{\gamma_1} \hat{\lambda}_1 \leq -\frac{\sigma_1 b_m \tilde{\lambda}_1^2}{2\gamma_1} + \frac{\sigma_1 b_m \lambda_1^{*2}}{2\gamma_1},$$

可得

$$\dot{V}_1 \leq -\left(b_m k_{11} - \frac{1}{2}\right) e_1^2 - b_m k_{12}(t) e_1^2 - \frac{\sigma_1 b_m \tilde{\lambda}_1^2}{2\gamma_1} + g_1(x_1) e_1 e_2 + \frac{U_1}{2(1-\bar{\tau}_{\max})} \left(1 - \frac{e_1^2}{c_1^2}\right) + \mu_{10}, \quad (18)$$

$$\text{其中 } \mu_{10} = \frac{\varepsilon_1^2}{2} + \frac{\sigma_1 b_m \lambda_1^{*2}}{2\gamma_1} + \frac{\eta_1^2}{2} + \frac{a_{11}^2}{2}.$$

Step 2 ($2 \leq i \leq n-1$) 考虑第 i 个子系统的误差方程 $e_i = x_i - \alpha_{i-1}$. 定义标量函数 $V_{e_i} = e_i^2/2$, 则有

$$\dot{V}_{e_i} = e_i g_i(\bar{x}_i) x_{i+1} + e_i \left\{ f_i(\bar{x}_i) + h_i(\bar{x}_{\tau_i}) + d_i(t, x) - \sum_{j=1}^{i-1} \frac{\partial \alpha_{i-1}}{\partial x_j} (h_j(\bar{x}_{\tau_j}) + d_j(t, x)) - W_{i-1} \right\}. \quad (19)$$

其中

$$W_{i-1} = \sum_{j=1}^{i-1} \frac{\partial \alpha_{i-1}}{\partial x_j} (f_j(\bar{x}_j) + g_j(\bar{x}_j) x_{j+1}) + \omega_{i-1},$$

$$\omega_{i-1} = \sum_{j=1}^{i-1} \frac{\partial \alpha_{i-1}}{\partial \hat{\lambda}_j} \dot{\lambda}_j + \frac{\partial \alpha_{i-1}}{\partial \bar{y}_{d,i-1}} \dot{\bar{y}}_{d,i-1} +$$

$$\frac{\partial \alpha_{i-1}}{\partial k_{i-1,m}(t)} \dot{k}_{i-1,m}(t),$$

$$k_{i-1,m}(t) = \sum_{j=1}^{i-1} \sum_{k=1}^j \int_{t-\tau_{\max}}^t \rho_{j,k}^2(x_k(\tau)) d\tau.$$

这里: ω_{i-1} 为可直接计算的量, W_{i-1} 为可用神经网络逼近的量.

注 2 在文献 [11-12,14] 中, 利用复合函数求导规则对虚拟控制 α_{i-1} 求导时未对虚拟控制中的时滞项 $k_{i-1}(t)$ 求偏导, 但如果直接对 $k_{i-1}(t)$ 求偏导, 整个求导过程又会变得十分复杂而无法实现. 本文将 $k_{i-1}(t)$ 中的 $\sum_{j=1}^{i-1} \sum_{k=1}^j \int_{t-\tau_{\max}}^t \rho_{j,k}^2(x_k(\tau)) d\tau$ 分离出来, 并将 $k_{i-1,m}(t) = \sum_{j=1}^{i-1} \sum_{k=1}^j \int_{t-\tau_{\max}}^t \rho_{j,k}^2(x_k(\tau)) d\tau$ 作为一个新的中间变量, 从而保证了虚拟控制求导的正确性.

利用假设 2, 假设 5 及 Young's 不等式可知

$$\begin{aligned} e_i h_i(\bar{x}_{\tau_i}) &\leq \\ |e_i \theta_i| \sum_{k=1}^i \rho_{i,k}(x_k(t - \tau_k(t))) &\leq \\ \sum_{k=1}^i \frac{\theta_i^2 e_i^2}{2} + \sum_{k=1}^i \frac{1}{2} \rho_{i,k}^2(x_k(t - \tau_k(t))), & \\ e_i d_i(t, x) &\leq \frac{m_i^2(\bar{x}_i) e_i^2}{2a_{ii}^2} + \frac{a_{ii}^2}{2}, \\ -e_i \sum_{j=1}^{i-1} \frac{\partial \alpha_{i-1}}{\partial x_j} h_j(\bar{x}_{\tau_j}) &\leq \end{aligned}$$

$$\sum_{j=1}^{i-1} \sum_{k=1}^j \frac{\theta_j^2 e_i^2}{2} \left(\frac{\partial \alpha_{i-1}}{\partial x_j} \right)^2 +$$

$$\sum_{j=1}^{i-1} \sum_{k=1}^j \frac{1}{2} \rho_{j,k}^2(x_k(t - \tau_k(t))),$$

$$-e_i \sum_{j=1}^{i-1} \frac{\partial \alpha_{i-1}}{\partial x_j} d_j(t, x) \leq$$

$$\sum_{j=1}^{i-1} \frac{m_j^2(\bar{x}_j) e_i^2}{2a_{ij}^2} \left(\frac{\partial \alpha_{i-1}}{\partial x_j} \right)^2 + \sum_{j=1}^{i-1} \frac{a_{ij}^2}{2},$$

其中 a_{ij} ($j = 1, 2, \dots, i$) 为任意给定的正常数.

将上式代入式 (19) 可得

$$\dot{V}_{e_i} \leq e_i \left\{ f_i(\bar{x}_i) + \sum_{k=1}^i \frac{\theta_k^2 e_i}{2} + \frac{m_i^2(\bar{x}_i) e_i}{2a_{ii}^2} +$$

$$\sum_{j=1}^{i-1} \sum_{k=1}^j \frac{\theta_j^2 e_i}{2} \left(\frac{\partial \alpha_{i-1}}{\partial x_j} \right)^2 +$$

$$\sum_{j=1}^{i-1} \frac{m_j^2(\bar{x}_j) e_i}{2a_{ij}^2} \left(\frac{\partial \alpha_{i-1}}{\partial x_j} \right)^2 - W_{i-1} \right\} +$$

$$e_i g_i(\bar{x}_i) x_{i+1} + \sum_{j=1}^i \sum_{k=1}^j \frac{1}{2} \rho_{j,k}^2(x_k(t -$$

$$\tau_k(t)) + \frac{1}{2} \sum_{j=1}^i a_{ij}^2. \quad (20)$$

为了消除式 (20) 中的时变时滞不确定项, 定义如下 Lyapunov-krasovskii 泛函:

$$V_{U_i} = \frac{1}{2(1-\bar{\tau}_{\max})} \sum_{j=1}^i \sum_{k=1}^j \int_{t-\tau_k(t)}^t \rho_{j,k}^2(x_k(\tau)) d\tau,$$

则有

$$\dot{V}_{e_i} + \dot{V}_{U_i} \leq$$

$$e_i \varphi_i(Z_i) + e_i g_i(\bar{x}_i) x_{i+1} - g_{i-1}(\bar{x}_{i-1}) e_{i-1} e_{i-1} +$$

$$\sum_{j=1}^i \frac{a_{ij}^2}{2} + \frac{1}{2(1-\bar{\tau}_{\max})} \left(1 - \frac{e_i^2}{c_i^2}\right) U_i. \quad (21)$$

其中

$$U_i = \sum_{j=1}^i \sum_{k=1}^j \rho_{j,k}^2(x_k(t)),$$

$$\varphi_i(Z_i) = f_i(\bar{x}_i) + g_{i-1}(\bar{x}_{i-1}) e_{i-1} + \sum_{k=1}^i \frac{\theta_k^2 e_i}{2} +$$

$$\frac{m_i^2(\bar{x}_i) e_i}{2a_{ii}^2} + \sum_{j=1}^{i-1} \sum_{k=1}^j \frac{\theta_j^2 e_i}{2} \left(\frac{\partial \alpha_{i-1}}{\partial x_j} \right)^2 +$$

$$\sum_{j=1}^{i-1} \frac{m_j^2(\bar{x}_j) e_i}{2a_{ij}^2} \left(\frac{\partial \alpha_{i-1}}{\partial x_j} \right)^2 - W_{i-1} +$$

$$\frac{e_i U_i}{2(1-\bar{\tau}_{\max}) c_i^2}, \quad (22)$$

这里

$$Z_i = \left[\bar{x}_i^T, \alpha_{i-1}, \frac{\partial \alpha_{i-1}}{\partial \bar{x}_{i-1}^T}, \omega_{i-1} \right]^T \in R^{2i+1}.$$

由式 (2) 和 (21) 可知

$$\begin{aligned} \dot{V}_{e_i} + \dot{V}_{U_i} \leq & W_i^{*T} S_i(Z_i) e_i + \delta_i(Z_i) e_i + e_i g_i(\bar{x}_i) \times \\ & (e_{i+1} + \alpha_i) - g_{i-1}(\bar{x}_{i-1}) e_i e_{i-1} + \\ & \sum_{j=1}^i \frac{a_{ij}^2}{2} + \frac{U_i}{2(1-\bar{\tau}_{\max})} \left(1 - \frac{e_i^2}{c_i^2} \right). \end{aligned} \quad (23)$$

选择如下 Lyapunov 函数:

$$V_i = V_{e_i} + V_{U_i} + \frac{b_m}{2\gamma_i} \tilde{\lambda}_i^2.$$

利用 Young's 不等式及 $\lambda_i^* = b_m^{-1} \|W_i^*\|^2$, 结合式 (4) 和 (5) 可得

$$\begin{aligned} \dot{V}_i \leq & - \left(b_m k_{i1} - \frac{1}{2} \right) e_i^2 - b_m k_{i2}(t) e_i^2 - \frac{\sigma_i b_m \tilde{\lambda}_i^2}{2\gamma_i} + \\ & \frac{1}{2(1-\bar{\tau}_{\max})} \left(1 - \frac{e_i^2}{c_i^2} \right) U_i - g_{i-1}(\bar{x}_{i-1}) \times \\ & e_{i-1} e_i + g_i(\bar{x}_i) e_i e_{i+1} + \mu_{i0}, \end{aligned} \quad (24)$$

其中

$$\mu_{i0} = \frac{\varepsilon_i^2}{2} + \frac{\sigma_i b_m \lambda_i^{*2}}{2\gamma_i} + \frac{\eta_i^2}{2} + \sum_{j=1}^i \frac{a_{ij}^2}{2}.$$

Step n ($i = n$) 考虑第 n 个子系统的误差方程 $e_n = x_n - \alpha_{n-1}$. 定义 Lyapunov 函数

$$V_n = V_{e_n} + V_{U_n} + \frac{b_m}{2\gamma_n} \tilde{\lambda}_n^2.$$

其中

$$V_{e_n} = \frac{e_n^2}{2},$$

$$V_{U_n} = \frac{1}{2(1-\bar{\tau}_{\max})} \sum_{j=1}^n \sum_{k=1}^j \int_{t-\tau_k}^t \rho_{j,k}^2(x_k(\tau)) d\tau.$$

采用如下控制律:

$$u = - \frac{\hat{\lambda}_n}{2\eta_n^2} \|S_n(Z_n)\|^2 e_n - s_n e_n. \quad (25)$$

则类似于 Step i 中的推导过程, 可得

$$\begin{aligned} \dot{V}_n \leq & - \left(b_m k_{n1} - \frac{1}{2} \right) e_n^2 - b_m k_{n2}(t) e_n^2 - \\ & \frac{\sigma_n b_m \tilde{\lambda}_n^2}{2\gamma_n} + \frac{1}{2(1-\bar{\tau}_{\max})} \left(1 - \frac{e_n^2}{c_n^2} \right) U_n - \\ & g_{n-1}(\bar{x}_{n-1}) e_{n-1} e_n + \mu_{n0}, \end{aligned} \quad (26)$$

其中

$$\mu_{n0} = \frac{\varepsilon_n^2}{2} + \frac{\sigma_n b_m \lambda_n^{*2}}{2\gamma_n} + \frac{\eta_n^2}{2} + \sum_{j=1}^n \frac{a_{nj}^2}{2}.$$

4 稳定性分析

定义紧集 $\Omega_{c_i} = \{x_i | e_i\} \leq c_i\}$. 其中 c_i 为正的设计常数, 它可以选择任意小.

定理 1 考虑系统 (1), 其控制律及自适应律由式 (4), (5) 和 (25) 确定, 并满足假设 1~ 假设 5, 则在

$\hat{\lambda}_i(t_0) \geq 0 (i = 1, 2, \dots, n)$ 的条件下, 闭环系统是半全局一致终结有界的, 且跟踪误差 $e = [e_1, e_2, \dots, e_n]^T \in \Omega_e$. 其中

$$\begin{aligned} \Omega_e = \left\{ e \mid \sum_{i=1}^n e_i^2 \leq B_e, i = 1, 2, \dots, n, \forall t \geq t_0 \right\}, \\ \hat{\lambda}_i \in \Omega_\lambda, \end{aligned}$$

这里

$$\Omega_\lambda = \left\{ \hat{\lambda}_i \mid \sum_{i=1}^n \tilde{\lambda}_i^2 \leq B_\lambda, i = 1, 2, \dots, n, \forall t \geq t_0 \right\},$$

B_e 及 B_λ 的定义将在稍后的证明中给出.

证明 考虑如下 Lyapunov 函数:

$$V = \sum_{i=1}^n V_i = \sum_{i=1}^n \left(V_{e_i} + V_{U_i} + \frac{b_m}{2\gamma_i} \tilde{\lambda}_i^2 \right). \quad (27)$$

下面分 3 种情况来完成证明.

情况 1 $|e_i| \leq c_i (\forall i = 1, 2, \dots, n)$, 则有

$$\sum_{i=1}^n e_i^2 \leq \sum_{i=1}^n c_i^2. \quad (28)$$

将 V 对时间 t 求导, 并利用式 (6), (24) 可得

$$\begin{aligned} \dot{V} \leq & \sum_{i=1}^n \left\{ - \left(b_m k_{i1} - \frac{1}{2} \right) e_i^2 - \frac{b_m k_{i3} e_i^2}{2(1-\bar{\tau}_{\max})(e_i^2 + c_i^2)} \times \right. \\ & \sum_{j=1}^i \sum_{k=1}^j \int_{t-\tau_{\max}}^t \rho_{j,k}^2(x_k(\tau)) d\tau - \frac{\sigma_i b_m \tilde{\lambda}_i^2}{2\gamma_i} - \\ & g_{i-1}(\bar{x}_{i-1}) e_{i-1} e_i + g_i(\bar{x}_i) e_i e_{i+1} + \\ & \left. \frac{1}{2(1-\bar{\tau}_{\max})} \left(1 - \frac{e_i^2}{c_i^2} \right) U_i + \mu_{i0} \right\}. \end{aligned} \quad (29)$$

其中: $e_0 = 0, e_{n+1} = 0$. 由于 $|e_i| \leq c_i (\forall i = 1, 2, \dots, n)$, 则有

$$\begin{aligned} - \frac{b_m k_{i3} e_i^2}{\beta_i} \sum_{j=1}^i \sum_{k=1}^j \int_{t-\tau_{\max}}^t \rho_{j,k}^2(x_k(\tau)) d\tau \leq \\ - b_m k_{i3} V_{U_i} + \frac{b_m k_{i3} c_i^2}{\beta_i} \sum_{j=1}^i \sum_{k=1}^j \int_{t-\tau_{\max}}^t \rho_{j,k}^2(x_k(\tau)) d\tau. \end{aligned} \quad (30)$$

注 3 由 e_1 和 y_d 有界可知 x_1 有界, 从而得到 $\frac{\gamma_1}{2\eta_1^2} S^T(Z_1) S(Z_1) e_1^2$ 是有界的. 由式 (5) 可知 $\hat{\lambda}_1$ 有界, 再由式 (4) 可知 α_1 有界, 而 $e_2 = x_2 - \alpha_1$, 则可知 x_2 有界. 同样, 由式 (5) 可知 $\hat{\lambda}_2$ 有界, 再由式 (4) 推出 α_2 有界, 依此类推 x_3, x_4, \dots, x_n 都是有界的.

由前面的假设可知 $\rho_{i,k}(x_k(t))$ 为连续函数, 令

$$\rho_{i,\max} = \sum_{j=1}^i \sum_{k=1}^j \max_{x_k \in \Omega_{c_k}} \rho_{j,k}^2(x_k(t)),$$

则有

$$\dot{V} \leq \sum_{i=1}^n \left\{ - \left(b_m k_{i1} - \frac{1}{2} \right) e_i^2 - b_m k_{i3} V_{U_i} - \right.$$

$$\left. \frac{\sigma_i b_m \tilde{\lambda}_i^2}{2\gamma_i} \right\} + \mu_1, \tag{31}$$

其中

$$\mu_1 = \sum_{i=1}^n \left\{ \frac{b_m k_{i3} \tau_{\max} + 1}{2(1 - \bar{\tau}_{\max})} \rho_{i, \max} + \mu_{i0} \right\}.$$

由式(31)可知

$$\dot{V} \leq -a_1 V + \mu_1, \tag{32}$$

其中

$$a_1 = \min \{ 2b_m k_{11} - 1, \dots, 2b_m k_{n1} - 1, b_m k_{13}, \dots, b_m k_{n3}, \sigma_1, \dots, \sigma_n \}.$$

令 $\rho_1 = \mu_1/a_1$, 则有

$$V(t) \leq V(t_0)e^{\mu_1(t_0-t)} + \rho_1. \tag{33}$$

由式(33)可知

$$\sum_{i=1}^n \tilde{\lambda}_i^2 \leq \frac{2\gamma}{b_m} (V(t_0) + \rho_1), \tag{34}$$

其中 $\gamma = \max \{ \gamma_1, \gamma_2, \dots, \gamma_n \}$.

情况 2 $|e_i| > c_i (\forall i = 1, 2, \dots, n)$, 由于 $|e_i| > c_i$,

则有

$$\begin{aligned} & -\frac{b_m k_{i3} e_i^2}{\beta_i} \sum_{j=1}^i \sum_{k=1}^j \int_{t-\tau_{\max}}^t \rho_{j,k}^2(x_k(\tau)) d\tau \leq \\ & -\frac{1}{2} b_m k_{i3} V_{U_i}. \end{aligned} \tag{35}$$

将式(35)代入(29), 可得

$$\begin{aligned} \dot{V} \leq \sum_{i=1}^n \left\{ -\left(b_m k_{i1} - \frac{1}{2}\right) e_i^2 - \frac{1}{2} k_{i3} b_m V_{U_i} - \right. \\ \left. - \frac{\sigma_i b_m \tilde{\lambda}_i^2}{2\gamma_i} + \mu_{i0} \right\}. \end{aligned} \tag{36}$$

类似上述方法, 可得

$$V(t) \leq V(t_0)e^{\mu_2(t_0-t)} + \rho_2. \tag{37}$$

其中

$$a_2 = \min \left\{ 2b_m k_{11} - 1, \dots, 2b_m k_{n1} - 1, \frac{1}{2} b_m k_{13}, \dots, \frac{1}{2} b_m k_{n3}, \sigma_1, \dots, \sigma_n \right\},$$

$$\rho_2 = \frac{\mu_2}{a_2}, \mu_2 = \sum_{i=1}^n \mu_{i0}.$$

则有

$$\sum_{i=1}^n e_i^2 \leq 2(V(t_0) + \rho_2), \tag{38}$$

$$\sum_{i=1}^n \tilde{\lambda}_i^2 \leq \frac{2\gamma}{b_m} (V(t_0) + \rho_2), \tag{39}$$

其中 $\gamma = \max \{ \gamma_1, \gamma_2, \dots, \gamma_n \}$.

情况 3 令

$$\begin{aligned} \Sigma_J &= \{ j : |e_j| > c_j, j = 1, 2, \dots, n \}, \\ \Sigma_I &= \{ i : |e_i| \leq c_i, i = 1, 2, \dots, n \}, \end{aligned}$$

则对于

$$\Sigma_J = \{ j : |e_j| > c_j, j = 1, 2, \dots, n \}$$

定义如下 Lyapunov 函数:

$$V_{\Sigma_J} = \sum_{j \in \Sigma_J} V_j = \sum_{j \in \Sigma_J} \left(V_{e_j} + V_{U_j} + \frac{b_m}{2\gamma_j} \tilde{\lambda}_j^2 \right). \tag{40}$$

对上式进行求导可得

$$\begin{aligned} \dot{V}_{\Sigma_J} \leq \sum_{j \in \Sigma_J} \left\{ \left(\frac{1}{2} - b_m k_{j1} \right) e_j^2 - b_m k_{j2}(t) e_j^2 - \right. \\ \left. \frac{\sigma_j b_m \tilde{\lambda}_j^2}{2\gamma_j} + \frac{1}{2(1 - \bar{\tau}_{\max})} \left(1 - \frac{e_j^2}{c_j^2} \right) U_j \right\} + \\ \sum_{j \in \Sigma_J} \mu_{j0} + \sum_{j \in \Sigma_J} \{ g_j(\bar{x}_j) e_{j+1} - \\ g_{j-1}(\bar{x}_{j-1}) e_{j-1} \} e_j. \end{aligned} \tag{41}$$

其中: $e_0 = 0, e_{n+1} = 0$,

$$\begin{aligned} & \sum_{j \in \Sigma_J} \{ g_j(\bar{x}_j) e_{j+1} e_j - g_{j-1}(\bar{x}_{j-1}) e_j e_{j-1} \} = \\ & \sum_{\substack{j \in \Sigma_J, \\ j+1 \in \Sigma_I}} g_j(\bar{x}_j) e_{j+1} e_j - \sum_{\substack{j \in \Sigma_J, \\ j-1 \in \Sigma_I}} g_{j-1}(\bar{x}_{j-1}) e_j e_{j-1} + \\ & \sum_{\substack{j \in \Sigma_J, \\ j+1 \in \Sigma_J}} g_j(\bar{x}_j) e_{j+1} e_j - \sum_{\substack{j \in \Sigma_J, \\ j-1 \in \Sigma_J}} g_{j-1}(\bar{x}_{j-1}) e_j e_{j-1}. \end{aligned} \tag{42}$$

经论证, 式(42)的最后两项可在后推设计中抵消, 根据假设 4 中 $g_i(x_i) \leq b_M < \infty (i = 1, 2, \dots, n)$ 可得

$$\begin{aligned} & \sum_{\substack{j \in \Sigma_J, \\ j+1 \in \Sigma_I}} g_j(\bar{x}_j) e_{j+1} e_j - \sum_{\substack{j \in \Sigma_J, \\ j-1 \in \Sigma_I}} g_{j-1}(\bar{x}_{j-1}) e_j e_{j-1} \leq \\ & \sum_{\substack{j \in \Sigma_J, \\ j+1 \in \Sigma_I}} \left(\frac{e_j^2}{2} + \frac{b_M^2 e_{j+1}^2}{2} \right) + \sum_{\substack{j \in \Sigma_J, \\ j-1 \in \Sigma_I}} \left(\frac{e_j^2}{2} + \frac{b_M^2 e_{j-1}^2}{2} \right) \leq \\ & \sum_{j \in \Sigma_J} \frac{e_j^2}{2} + \sum_{j+1 \in \Sigma_I} \frac{b_M^2 c_{j+1}^2}{2} + \\ & \sum_{j \in \Sigma_J} \frac{e_j^2}{2} + \sum_{j-1 \in \Sigma_I} \frac{b_M^2 c_{j-1}^2}{2} \leq \\ & \sum_{j \in \Sigma_J} e_j^2 + \sum_{j \in \Sigma_I} b_M^2 c_j^2. \end{aligned} \tag{43}$$

则由式(41)~(43)可得

$$\begin{aligned} \dot{V}_{\Sigma_J} \leq \sum_{j \in \Sigma_J} \left\{ -\left(b_m k_{j1} - \frac{3}{2}\right) e_j^2 - b_m k_{j2}(t) e_j^2 - \right. \\ \left. \frac{\sigma_j b_m \tilde{\lambda}_j^2}{2\gamma_j} + \frac{1}{2(1 - \bar{\tau}_{\max})} \left(1 - \frac{e_j^2}{c_j^2} \right) U_j \right\} + \mu_J, \end{aligned} \tag{44}$$

其中 $\mu_J = \sum_{j \in \Sigma_J} \mu_{j0} + \sum_{j \in \Sigma_I} b_M^2 c_j^2$.

类似情况 2 的推导可知

$$V_{\Sigma_J}(t) \leq V_{\Sigma_J}(t_0)e^{\mu_J(t_0-t)} + \rho_J. \tag{45}$$

由式 (45) 可知

$$\sum_{j \in \Sigma_J} e_j^2 \leq 2(V_{\Sigma_J}(t_0) + \rho_J), \quad (46)$$

$$\sum_{j \in \Sigma_J} \tilde{\lambda}_j^2 \leq \frac{2\gamma}{b_m}(V_{\Sigma_J}(t_0) + \rho_J), \quad (47)$$

其中 $\gamma = \max_{j \in \Sigma_J} \{\gamma_j\}$. 由以上分析可知 $\sum_{i=1}^n e_i^2 \leq B_e$. 其中

$$B_e = \max \left\{ \sum_{i=1}^n c_i^2, 2V(t_0) + 2\rho_2, 2V_{\Sigma_J}(t_0) + 2\rho_J + \sum_{i \in \Sigma_I} c_i^2 \right\}.$$

定义如下 Lyapunov 函数:

$$V_{\Sigma_I} = \sum_{j \in \Sigma_I} (V_{e_i} + V_{U_i}(t) + \frac{b_m}{2\gamma_i} \tilde{\lambda}_i^2).$$

由于已证得 $\sum_{i=1}^n e_i^2 \leq B_e$, 则类似于情况 1 的证明有

$$\sum_{i \in \Sigma_I} \tilde{\lambda}_i^2 \leq \frac{2\gamma}{b_m}(V_{\Sigma_I}(t_0) + \rho_I), \quad (48)$$

其中 $\gamma = \max_{i \in \Sigma_I} \{\gamma_i\}$.

综合情况 1~ 情况 3 可知, $\sum_{i=1}^n \tilde{\lambda}_i^2 \leq B_\lambda$, 其中

$$B_\lambda = \max \left\{ \frac{2\gamma}{b_m}(V(t_0) + \rho_1), \frac{2\gamma}{b_m}(V(t_0) + \rho_2), \frac{2\gamma}{b_m}(V_{\Sigma_I}(t_0) + \rho_I) + \frac{2\gamma}{b_m}(V_{\Sigma_J}(t_0) + \rho_J) \right\}. \quad \square$$

5 仿真算例

为了验证所提算法的有效性, 考虑如下二阶时滞系统:

$$\begin{cases} \dot{x}_1 = (1 + x_1^2)x_2 + x_1 e^{-0.5x_1} + 2x_1^2(t - \tau_1(t)) + 0.6x \sin t, \\ \dot{x}_2 = (3 + \cos(x_1x_2))u + x_1x_2^2 + 0.2x_2(t - \tau_2(t)) \sin(x_2(t - \tau_2)) + 0.5(x_1^2 + x_2^2) \sin^3 t, \\ y = x_1. \end{cases} \quad (49)$$

控制目标是使得系统输出 y 跟踪期望的轨迹 $y_d = 0.5(\sin t + \sin(0.5t))$.

仿真中时变时滞为

$$\tau_1(t) = 0.2(1 + \sin t), \tau_2(t) = 1 - 0.5 \cos t,$$

$$\tau_{\max} = 2, \bar{\tau}_{\max} = 0.5, \rho_{1,1}(x_1) = x_1^2,$$

$$\rho_{2,1}(x_1) = 0, \rho_{2,2}(x_2) = |x_2|, m_1(x) = 0.6|x_1|,$$

$$m_2(x) = 0.5(x_1^2 + x_2^2), Z_1 = [x_1, y_d, \dot{y}_d]^T,$$

$$Z_2 = [x_1, x_2, \alpha_1, \partial\alpha_1/\partial x_1, \omega_1]^T.$$

节点数分别选为 $l_1 = 50, l_2 = 60$, 基函数的中心为

$$\mu_{1j} = 0.02(j - 25)[1, 1, 1]^T, j = 1, 2, \dots, l_1;$$

$$\mu_{2j} = 0.03(j - 30)[1, 1, 1, 1, 1]^T, j = 1, 2, \dots, l_2.$$

宽度 $\phi_{ij} = 1 (j = 1, 2, \dots, l_i, i = 1, 2), k_{11} = k_{21} = 60, c_1 = c_2 = 0.01, \eta_1 = \eta_2 = 1, k_{13} = 0.001, k_{23} = 0.0001, \gamma_1 = \gamma_2 = 3, \sigma_1 = \sigma_2 = 0.05$, 初始状态向量 $[x_1(0), x_2(0)]^T = [0, 0]^T$, 自适应参数初值为 $[\hat{\lambda}_1(0), \hat{\lambda}_2(0)]^T = [0.2, 0.2]^T$, 仿真结果如图 1~ 图 3 所示. 图 1 表明本文提出的控制算法具有良好的跟踪性能, 其中实线代表状态变量 x_1 , 虚线代表期望输出 y_d ; 图 2 中实线代表自适应调节参数 $\hat{\lambda}_1$, 虚线代表 $\hat{\lambda}_2$.

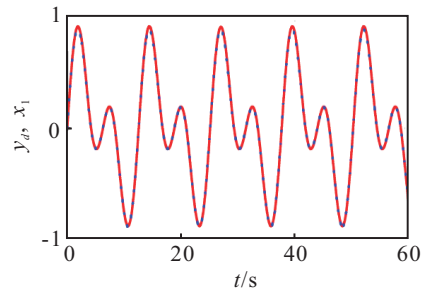


图 1 状态变量 x_1 和期望输出 y_d

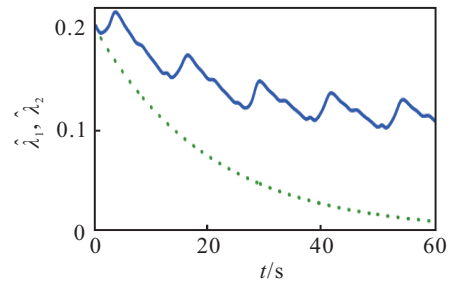


图 2 自适应调节参数 $\hat{\lambda}_1$ 和 $\hat{\lambda}_2$

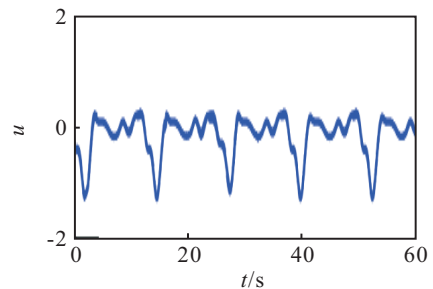


图 3 控制信号 u

6 结 论

对一类具有时变时滞的严格反馈非线性系统, 利用径向基函数神经网络、后推设计和 Young's 不等式, 提出了一种自适应神经网络跟踪控制方案. 该方案放宽了对时滞不确定项的假设, 避免了设计实用控制器时所构造的待逼近函数在原点的不连续性. 此外, 在后推的每一步, 只有一个参数需要在线调节, 这样降低了实现的复杂性. 通过理论分析, 结果表明了所设计的自适应控制器能保证闭环系统是一致终结有界的, 且跟踪误差收敛到原点的一个邻域内. 仿真结果表明了本文算法的有效性.

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