第23卷 第10期 控 制 与 决 策 2008年10月
Vol. 23 No. 10 Control and Decision Oct. 2008

文章编号: 1001-0920(2008)10-1153-06

控制增益符号未知的MIMO时滞系统自适应控制

钱厚斌[a,b], 张天平[a]
(扬州大学 a. 信息工程学院, b. 新闻与传媒学院, 江苏 扬州 225009)

摘 要: 针对一类带有死区模型并具有未知函数控制增益的不确定MIMO非线性时滞系统,基于滑模控制原理和Nussbaum函数的性质,提出了一种稳定的自适应神经网络控制方案. 该方案放宽了对函数控制增益上界为未知常数的假设,并通过使用Lyapunov-Krasovskii泛函抵消了因未知时变时滞带来的系统不确定性. 理论分析证明,闭环系统是半全局一致终结有界. 仿真结果表明了该方法的有效性.

关键词: 自适应控制; 神经网络; 滑模控制; 时变时滞
中图分类号: TP273 **文献标识码**: A

Adaptive control of MIMO nonlinear time-varying delay systems with unknown gain signs

QIAN Hou-bin[a,b], *ZHANG Tian-ping*[a]
(a. College of Information Engineering, b. College of Journalism and Communication, Yangzhou University, Yangzhou 225009, China. Correspondent: ZHANG Tian-ping, E-mail: tpzhang@yzu.edu.cn)

Abstract: A design scheme of adaptive neural controller for a class of uncertain MIMO nonlinear time-varying delay systems with unknown nonlinear dead-zones and unknown function control gain is proposed, based on the principle of sliding mode control and property of Nussbaum-type functions. The approach relaxes the hypothesis that the upper bound of function control gain is unknown constant. The unknown time-varying delay uncertainties are compensated for using appropriate Lyapunov-Krasovskii functionals in the design. By using theoretical analysis, the closed-loop control systems is proved to be semi-globally uniformly ultimately bounded. Simulation results demonstrate the effectiveness of the approach.

Key words: Adaptive control; Neural networks; Sliding mode control; Time-varying delays

1 引 言

在许多工业过程中,死区非线性是系统中常见的一种非线性环节. 文献[1,2]针对一类线性系统,分别采用连续和离散的自适应死区逆对死区进行补偿. [3-5]针对含有死区模型的线性或非线性系统,提出了新的控制方案. 其中[4,5]通过简化死区模型使得控制律的设计更为简单,然而[4]仅讨论了死区模型为线性的模型参考自适应控制问题,[6]只讨论了控制增益为常数且死区的斜率相等的情况. [7]针对一类具有时滞和死区输入的大系统,提出了一种分散变结构自适应控制策略,但方法要求死区参数和控制增益均为已知常数,而该条件往往因为先验知识不足而无法满足.

在各类工业系统中,时滞现象是普遍存在的. 时滞系统的稳定性问题一直受到人们的广泛关注. 非线性系统时滞(或时间延迟)对各类工程系统的控制性能会产生重要影响,在这一领域已经取得了一些重要成果. 文献[8,9]针对一类非线性时滞系统,利用[10]的Lyapunov-Krasovskii泛函性质来补偿未知时滞的不确定性,提出自适应神经网络控制方案. [11]研究了一类具有未知死区和控制增益符号的MIMO非线性时变时滞系统的鲁棒自适应神经网络控制问题.

本文在文献[11]的基础上,针对一类具有未知死区和控制增益符号未知的MIMO非线性时变时滞系统,引入与[11]中不同的积分型Lyapunov函

收稿日期: 2007-07-26; **修回日期**: 2007-11-03.
基金项目: 国家自然科学基金项目(60774017); 江苏省教育厅自然科学基金项目(07KJB520133).
作者简介: 钱厚斌(1973—),男,江苏姜堰人,助理研究员,硕士,从事自适应控制、神经网络控制等研究; 张天平(1964—),男,江苏泰兴人,教授,博士,从事自适应控制、模糊控制等研究.

数,提出一种稳定的自适应神经网络控制方案.该方案只需要控制增益上界为已知函数的假设,从而放宽了[11]中对控制增益上界为未知常数的假设.进一步引入连续函数,避免了逼近函数的不连续性现象.通过理论分析证明,闭环系统是半全局一致终结有界的.

2 问题描述及基本假设

2.1 问题的描述

考虑下面一类 MIMO 时滞非线性系统:

$$\begin{aligned}
&\dot{x}_{1j} = x_{1,j+1},\ j = 1,2,\cdots,n_1 - 1;\\
&\dot{x}_{1n_1} = f_1(x) + g_{1,\tau}(x_1(t-\tau_1(t)),\\
&\qquad \cdots, x_m(t-\tau_m(t))) +\\
&\qquad b_1(x_1)u_1 + \Delta_{1,n_1}(x,t);\\
&\dot{x}_{ij} = x_{i,j+1},\ j = 1,2,\cdots,n_i - 1;\\
&\dot{x}_{in_i} = f_i(x,u_1,\cdots,u_{i-1}) + b_i(x_1,\cdots,x_i)u_i +\\
&\qquad \Delta_{i,n_i}(x,t) + g_{i,\tau}(x_1(t-\tau_1(t)),\cdots,\\
&\qquad x_m(t-\tau_m(t))),\ i = 2,3,\cdots,m;\\
&x_i(t) = \phi_i(t),\ t\in[-\tau_{\max},0],\ i = 1,2,\cdots,m;\\
&y_1 = x_{11},\ \cdots,\ y_m = x_{m1};
\end{aligned}\tag{1}$$

定义输入为 $v_i(t)$,输出为 $u_i(t)$ 的死区模型如下:

$$u_i(t) = D_i(v_i(t)) = \begin{cases} g_{ir}(v_i),\ v_i(t)\geq b_{ir};\\ 0,\ b_{il} < v_i(t) < b_{ir};\\ g_{il}(v_i),\ v_i(t)\leq b_{il}.\end{cases}\tag{2}$$

其中

$$x = [x_1^{\mathrm T}, x_2^{\mathrm T}, \cdots, x_m^{\mathrm T}]^{\mathrm T}\in R^n;$$
$$x_i = [x_{i1}, x_{i2}, \cdots, x_{in_i}]^{\mathrm T};$$
$$i = 1,2,\cdots,m,\ n = \sum_{i=1}^m n_i;$$

$g_{ir}(v_i)$ 和 $g_{il}(v_i)$ 是未知光滑非线性函数;y_i 是第 i 个子系统的输出;$f_1(x), f_2(x,u_1),\cdots,f_m(x,u_1,\cdots,u_{m-1})$ 和 $g_{i,\tau}(x_1(t-\tau_1(t)),\cdots,x_m(t-\tau_m(t)))$ 均是未知连续函数;$b_1(\bar{x}_1), b_2(\bar{x}_2),\cdots,b_m(\bar{x}_m)$ 是未知控制增益,$\bar{x}_i = [x_1^{\mathrm T}, x_2^{\mathrm T},\cdots,x_i^{\mathrm T}]^{\mathrm T}$;$\tau_1(t),\tau_2(t),\cdots,\tau_m(t)$ 是未知时变时滞;$\phi_1(t),\phi_2(t),\cdots,\phi_m(t)$ 是已知的初始状态向量函数;$\tau_{\max}$ 是已知正常数,将在后面定义中给出;$u_i\in R$ 是第 i 个死区的输出(是第 i 个系统的输入);$v_i(t)\in R$ 是第 i 个死区的输入,b_{il} 和 b_{ir} 是第 i 个死区的未知参数;$\Delta_{i,n_i}(x,t)$ 是外界干扰或未建模动态.

为设计稳定的自适应神经网络控制,作如下假设.

假设 1 死区输出 $u_1,u_2,\cdots,u_m$ 是不可测量的;

假设 2 死区参数 b_{ir} 和 b_{il} 为未知的有界常数,$b_{ir} > 0$, $b_{il} < 0$, $i = 1,2,\cdots,m$;

假设 3 $g_{il}(v_i)$ 和 $g_{ir}(v_i)$ 是光滑的,并且存在未知的正常数 $k_{il0}, k_{il1}, k_{ir0}, k_{ir1}$,满足

$$0 < k_{il0}\leq g_{il}'(v_i)\leq k_{il1},\ \forall v_i\in(-\infty, b_{il}],\tag{3}$$
$$0 < k_{ir0}\leq g_{ir}'(v_i)\leq k_{ir1},\ \forall v_i\in[b_{ir},+\infty).\tag{4}$$

其中

$$g_{il}'(v_i) = \mathrm{d}g_{il}(z)/\mathrm{d}z\,|_{z=v_i},$$
$$g_{ir}'(v_i) = \mathrm{d}g_{ir}(z)/\mathrm{d}z\,|_{z=v_i}.$$

为了分析的方便,死区可以重新定义为[11]

$$u_i(t) = D_i(v_i) = K_i^{\mathrm T}(t)\Phi_i(t)v_i + d_i(v_i).\tag{5}$$

其中

$$\Phi_i(t) = [\phi_{ir}(t), \phi_{il}(t)]^{\mathrm T};$$
$$K_i(t) = [g_{ir}'(\xi_{ir}(v_i(t))), g_{il}'(\xi_{il}((v_i(t)))]^{\mathrm T};$$
$$\phi_{ir}(t) = \begin{cases}1,\ v_i(t) > b_{il};\\ 0,\ v_i(t)\leq b_{il};\end{cases}$$
$$\phi_{il}(t) = \begin{cases}1,\ v_i(t)\leq b_{ir};\\ 0,\ v_i(t) > b_{ir};\end{cases}$$
$$d_i(v_i) = \begin{cases}-g_{ir}'(\xi_{ir}(v_i))b_{ir},\ v_i\geq b_{ir};\\ -[g_{il}'(\xi_{il}(v_i)) + g_{ir}'(\xi_{ir}(v_i))]v_i,\\ \qquad b_{il}\leq v_i\leq b_{ir};\\ -g_{il}'(\xi_{il}(v_i))b_{il},\ v_i\leq b_{il};\end{cases}$$

$|d_i(v_i)|\leq p_i^*$, $p_i^* = (k_{ir1} + k_{il1})\max\{b_{ir}, -b_{il}\}$ 是未知常数.

控制目标要求系统输出 y_i 尽可能好地去跟踪一个指定的期望轨迹 y_{id}.因此,需要设计一个控制律 $v_i(t)$,使得闭环系统一致终结有界,跟踪误差收敛到一个小的残差集内.定义

$$x_{id} = [y_{id},\cdots,y_{id}^{(n_i-1)}]^{\mathrm T},$$
$$e_i = x_i - x_{id} = [e_{i1}, e_{i2},\cdots,e_{in_i}]^{\mathrm T}.$$

滤波跟踪误差为

$$s_i = \left(\frac{\mathrm d}{\mathrm dt} + \lambda_i\right)^{n_i-1}e_{i1} = \sum_{j=1}^{n_i-1}\lambda_{ij}e_{ij} + e_{in_i}.\tag{6}$$

其中 $\lambda_{ij} = C_{n_i-1}^{j-1}\lambda_i^{n_i-j}$, $j = 1,2,\cdots,n_i-1$, $\lambda_i > 0$, $i = 1,2,\cdots,m$,由设计者选定.

假设 4 光滑函数 $b_i(\bar{x}_i)$ 符号未知,存在正常数 b_{i0} 和函数 $b_{i1}(\bar{x}_i)$,满足

$$0 < b_{i0}\leq|b_i(\bar{x}_i)|\leq b_{i1}(\bar{x}_i),\ \forall\bar{x}_i\in R^{\bar{n}_i},$$
$$\bar{n}_i = \sum_{j=1}^i n_j,\ i = 1,2,\cdots,m.$$

假设 5 $\bar{x}_{id} = [x_{id}^{\mathrm T}, y_{id}^{(n_i)}]^{\mathrm T}\in\Omega_{id}\subset R^{n_i+1}$,$\Omega_{id}$ 是一个已知的有界紧集,$i = 1,2,\cdots,m$.

假设 6 时滞不确定项满足

$$|g_{i,\tau}(x_1(t-\tau_1(t)),\cdots,x_m(t-\tau_m(t)))|\leq$$
$$\sum_{k=1}^m\rho_{ik}(x_k(t-\tau_k(t))).$$

其中 $\rho_{ik}(x_k(t))$ 为已知正连续函数,$i = 1,2,\cdots,m$.

假设 7　$0 \le \tau_i(t) \le \tau_{\max}$, $\dot{\tau}_i(t) \le \bar{\tau}_{\max} < 1$, $i = 1, 2, \cdots, m$, $\tau_{\max}$ 和 $\bar{\tau}_{\max}$ 均为已知常数.

假设 8　$|\Delta_{i,n_i}(x,t)| \le H^* N(\bar{x}_i)$, $N(\bar{x}_i)$ 是已知非负连续函数, H^* 是未知正常数.

2.2　Nussbaum 函数及其性质

为了处理控制增益符号未知,引入 Nussbaum 函数[12].

定义 1　如果连续函数 $N(s): R \to R$ 满足条件:

$$1)\ \lim_{s\to+\infty}\sup \frac{1}{s}\int_0^s N(\zeta)\,\mathrm{d}\zeta = +\infty, \tag{7}$$

$$2)\ \lim_{s\to-\infty}\inf \frac{1}{s}\int_0^s N(\zeta)\,\mathrm{d}\zeta = -\infty, \tag{8}$$

则称 $N(s)$ 是 Nussbaum 函数.

下面给出 Nussbaum 函数的性质.

定理 1　已知 $V(\cdot)$, $\zeta(\cdot)$ 都是 $[0, t_f)$ 上的光滑函数,且 $V(t) \ge 0$, $\forall t \in [0, t_f)$, $N(\cdot)$ 是 Nussbaum 函数,如果下列不等式成立:

$$V(t) \le c_0 + \mathrm{e}^{-c_1 t}\int_0^t g(\tau) N(\zeta)\dot{\zeta}\mathrm{e}^{c_1\tau}\mathrm{d}\tau + \mathrm{e}^{-c_1 t}\int_0^t \dot{\zeta}\mathrm{e}^{c_1\tau}\mathrm{d}\tau,\quad \forall t \in [0, t_f). \tag{9}$$

其中:常数 $c_1 > 0$; $g(t)$ 是一个取值在未知闭区间 $I := [l^{-1}, l^{+1}]$, $0 \notin I$ 上的时变参数; c_0 是适当的常数. 那么 $V(t)$, $\zeta(t)$ 和 $\int_0^t g(\tau) N(\zeta)\dot{\zeta}\mathrm{d}\tau$ 一定在 $[0, t_f)$ 上有界.

本文取 $N(\zeta) = \mathrm{e}^{\zeta^2}\cos(\pi\zeta/2)$, $(\tilde{\cdot}) = (\hat{\cdot}) - (\cdot)^*$.

3　自适应神经网络控制器的设计

由式(1), (5), (6) 可得

$$\begin{aligned}\dot{s}_i = {} & f_i(x, u_1, \cdots, u_{i-1}) + b_i(\bar{x}_i) K_i^{\mathrm{T}}\Phi_i(t) v_i(t) + \\ & g_{i,\tau}(x_1(t-\tau_1(t)), \cdots, x_m(t-\tau_m(t))) + \\ & b_i(\bar{x}_i) d_i(v_i(t)) + \gamma_i + \Delta_{i,n_i}(x,t),\end{aligned} \tag{10}$$

其中 $\gamma_i = \sum_{j=1}^{n_i-1}\lambda_{ij} e_{i,j+1} - y_{id}^{(n_i)}$.

定义光滑函数

$$V_{s_i} = \int_0^{s_i} \sigma |\alpha_i(\bar{x}_i^+, \sigma + \beta_i)|\,\mathrm{d}\sigma. \tag{11}$$

其中

$$\alpha_i(\bar{x}_i) = b_{i1}(\bar{x}_i)/b_i(\bar{x}_i),$$

$$\beta_i = y_{id}^{(n_i-1)} - \sum_{j=1}^{n_i-1}\lambda_{ij} e_{i,j},$$

$$\bar{x}_i^+ = [x_1^{\mathrm{T}}, x_2^{\mathrm{T}}, \cdots, x_{i-1}^{\mathrm{T}}, x_{i1}, \cdots, x_{i,n_i-1}]^{\mathrm{T}}.$$

因为

$$0 < b_{i0} < |b_i(\bar{x}_i)| < b_{i1}(\bar{x}_i),$$

$$\frac{s_i^2}{2} \le V_{s_i} \le \frac{1}{b_{i_0}}\int_0^{s_i}\sigma b_{i1}(\bar{x}_i^+, \sigma + \beta_i)\,\mathrm{d}\sigma = \frac{s_i^2}{b_{i0}}\int_0^1 \omega b_{i1}(\bar{x}_i^+, \omega s_i + \beta_i)\,\mathrm{d}\omega. \tag{12}$$

所以有 $V_{si} \ge s_i^2/2 > 0$,即 V_{s_i} 是关于变量 s_i 的正定函数. 由复合函数的求导规则,及

$$\frac{\partial\alpha_i(\bar{x}_i^+, \sigma + \beta_i)}{\partial\beta_i} = \frac{\partial\alpha_i(\bar{x}_i^+, \sigma + \beta_i)}{\partial\sigma},$$

且 $\beta_i = -\gamma_i$,应用式(10) 可得

$$\begin{aligned}\dot{V}_{s_i} \le {} & s_i|\alpha_i(\bar{x}_i)|\, b_i(\bar{x}_i) K_i^{\mathrm{T}}(t)\Phi_i(t) v_i + s_i Q_i(z_i) + \\ & s_i|\alpha_i(\bar{x}_i)|\, g_{i,\tau}(x_1(t-\tau_1(x)), \cdots, x_m(t-\tau_m(t))) + |s_i|\, b_{i1} p_i^* + \sum_{j=1}^{i-1} g_{j,\tau}(x_1(t-\tau_1(t)), \cdots, x_m(t-\tau_m(t))) \times \\ & \int_0^{s_i}\sigma\frac{\partial|\alpha_i(\bar{x}_i, \sigma + \beta_i|)}{\partial x_{jn_j}}\mathrm{d}\sigma + |s_i|\,|\alpha_i(\bar{x}_i)|\, H_i^* N(\bar{x}_i).\end{aligned} \tag{13}$$

其中

$$\begin{aligned}Q_i(z_i) = {} & f_i(x, u_1, \cdots, u_{i-1})\,|a_i(\bar{x}_i)| + \int_0^1\theta\sum_{j=1}^{i}\sum_{k=1}^{n_i-1}\frac{\partial|\alpha_i(\bar{x}_i, \theta s_i + \beta_i|)}{\partial x_{jk}} x_{j,k+1} + \\ & \sum_{j=1}^{i-1}\frac{\partial|\alpha_i(\bar{x}_i, \theta s_i + \beta_i)|}{\partial x_{jn_j}}\theta \times [f_j(x, u_1, \cdots, u_{j-1}) + b_j(\bar{x}_j) D_j(v_j) + \\ & \Delta_{i,n_i}(x,t)] + \gamma_i|\alpha_i(\bar{x}_i^+, \theta s_i + \beta_i)|\}\,\mathrm{d}\theta.\end{aligned} \tag{14}$$

$$z_i = [x^{\mathrm{T}}, s_i, \gamma_i, \beta_i, v_1, \cdots, v_{i-1}]^{\mathrm{T}} = [z_{i1}, z_{i2}, \cdots, z_{ip_i}]^{\mathrm{T}},$$

$$p_i = n + i + 2.$$

利用假设 6 及 Young's 不等式,有

$$\begin{aligned}& \sum_{j=1}^{i-1} g_{j,\tau}(x_1(t-\tau_1(t)), \cdots, x_m(t-\tau_m(t))) \times \int_0^{s_i}\sigma\frac{\partial|\alpha_i(\bar{x}_i, \sigma + \beta_i)|}{\partial x_{jn_j}}\mathrm{d}\sigma \le \\ & \frac{m}{2}\sum_{j=1}^{i-1}\sum_{k=1}^{m}\rho_{jk}^2(x_k(t-\tau_k(t))) + \frac{s_i^4}{2}\sum_{j=1}^{i-1}\left(\int_0^1\theta\frac{\partial|\alpha_i(\bar{x}_i^+, \theta s_i + \beta_i)|}{\partial x_{jn_j}}\mathrm{d}\theta\right)^2.\end{aligned} \tag{15}$$

$$\begin{aligned}& s_i g_{i,\tau}(x_1(t-\tau_1(t)), \cdots, x_m(t-\tau_m(t)))\,|\alpha_i(\bar{x}_i)| \le \\ & \frac{s_i^2\alpha_i^2(\bar{x}_i)}{2} + \frac{m}{2}\sum_{k=1}^{m}\rho_{ik}^2(x_k(t-\tau_k(t))).\end{aligned} \tag{16}$$

将式(15) 和(16) 代入(13),得

$$\dot{V}_{s_i} \le$$

$$s_i|\alpha_i(\bar{x}_i)|b_i(\bar{x}_i)K_i^{\mathrm{T}}(t)\Phi_i(t)v_i+s_iQ_i(z_i)+\frac{s_i^2b_{il}^2}{2}+\frac{s_i^2\alpha_i^2(\bar{x}_i)+s_i^2\alpha_i^2(\bar{x}_i)N^2(\bar{x}_i)}{2}+\frac{p_i^{*2}+H_i^{*2}}{2}+\frac{s_i^4}{2}\sum_{j=1}^{i-1}\Big(\int_0^1\theta\frac{\partial|\alpha_i(\bar{x}_i^+,\theta s_i+\beta)|}{\partial x_{jn_j}}\mathrm{d}\theta\Big)^2+\frac{m}{2}\sum_{j=1}^{i}\sum_{k=1}^{m}\rho_{jk}^2(x_k(t-\tau_k(t))).\quad(17)$$

为了克服未知时滞 $\tau_1(t),\tau_2(t),\cdots,\tau_m(t)$ 带来的困难,定义 Lyapunov-Krasovskii 泛函

$$V_{u_i}(t)=\frac{m}{2(1-\bar{\tau}_{\max})}\sum_{j=1}^{i}\sum_{k=1}^{m}\int_{t-\tau_k(t)}^{t}\rho_{jk}^2(x_k(\tau))\mathrm{d}\tau.\quad(18)$$

对式(18)求导,可得

$$\dot{V}_{u_i}(t)=\frac{m}{2(1-\bar{\tau}_{\max})}\sum_{j=1}^{i}\sum_{k=1}^{m}\rho_{jk}^2(x_k(t))-\frac{m}{2(1-\bar{\tau}_{\max})}\sum_{j=1}^{i}\sum_{k=1}^{m}\rho_{jk}^2(x_k(t-\tau_k(t)))(1-\dot{\tau}_k(t)).\quad(19)$$

则

$$\dot{V}_{s_i}+\dot{V}_{u_i}(t)\leq s_iB_i(t)v_i+s_ih_i(z_i)+\frac{p_i^{*2}+H_i^{*2}}{2}+\frac{m}{2(1-\bar{\tau}_{\max})}\Big[1-\frac{s_i^2}{c_{s_i}^2}\Big]\sum_{j=1}^{i}\sum_{k=1}^{m}\rho_{jk}^2(x_k(t)).\quad(20)$$

其中:$B_i(t)=|\alpha_i(\bar{x}_i)|b_i(\bar{x}_i)K_i^{\mathrm{T}}(t)\Phi_i(t)$,$c_{s_i}>0$ 是设计正常数,而

$$h_i(z_i)=Q_i(z_i)+\frac{s_i\alpha_i^2(\bar{x}_i)+s_i\alpha_i^2(\bar{x}_i)N^2(\bar{x}_i)}{2}+\frac{s_i^3}{2}\sum_{j=1}^{i-1}\Big(\int_0^1\theta\frac{\partial|\alpha_i(\bar{x}_i^+,\theta s_i+\beta)|}{\partial x_{jn_j}}\mathrm{d}\theta\Big)^2+\frac{s_ib_{il}^2}{2}+\frac{ms_i}{2(1-\bar{\tau}_{\max})c_{s_i}^2}\sum_{j=1}^{i}\sum_{k=1}^{m}\rho_{jk}^2(x_k(t)).\quad(21)$$

定义紧集

$$\Omega_{z_i}=\{[x^{\mathrm{T}},s_i,\gamma_i,\beta_i,v_1,v_2,\cdots,v_{i-1}]^{\mathrm{T}}|\ x_j\in\Omega_j,\ j=1,2,\cdots,m,\ \bar{x}_{kd}\in\Omega_{kd},k=1,2,\cdots,i\},\quad(22)$$

$$\Omega_{c_i}=\{x\,\|s_i|\leq c_{s_i},\bar{x}_{kd}\in\Omega_{kd},k=1,2,\cdots,i\}.\quad(23)$$

其中 $\Omega_j\in R^{n_j}$ 是一个足够大的紧集.

设 $h_i(z_i,\theta_i)$ 是径向基函数神经网络在闭区域 Ω_{z_i} 上对 $h_i(z_i)$ 的逼近,即 $h_i(z_i,\theta_i)=\theta_i^{\mathrm{T}}\xi_i(z_i)$. 其中:$\theta_i=(\theta_{i1},\cdots,\theta_{iN_i})^{\mathrm{T}}$ 是连结权向量,径向基向量 $\xi_i(z_i)=(\xi_{i1}(z_i),\cdots,\xi_{iN_i}(z_i))^{\mathrm{T}}$,基函数

$$\xi_{il}(z_i)=\exp\Big(-\frac{\sum_{j=1}^{p_i}(z_{ij}-a_{ij}^l)^2}{(b_i^l)^2}\Big),$$

$l=1,2,\cdots,N_i,b_i^l>0,\ a_{ij}^l\in R,\ j=1,2,\cdots,i$. 令

$$\Omega_{\theta_i}=\{\theta_i:\ \|\theta_i\|\leq M_{\theta_i}\},$$

$$\theta_i^*=\arg\min_{\theta_i\in\Omega_{\theta_i}}[\sup_{z_i\in\Omega_{z_i}}|h_i(z_i,\theta_i)-h_i(z_i)|],$$

其中正常数 M_{θ_i} 是设计参数. 对于未知函数 $h_i(z_i)$,可得

$$h_i(z_i)=\theta_i^{*\mathrm{T}}\xi_i(z_i)+\varepsilon_i^*(z_i),\quad(24)$$

其中神经网络逼近误差 $\varepsilon_i^*(z_i)$ 满足 $|\varepsilon_i^*(z_i)|\leq\varepsilon_i$,$i=1,2,\cdots,n$.

考虑如下控制律:

$$v_i(t)=\frac{N(\zeta_i)}{b_{i1}(\bar{x}_i)}[k_{i0}(t)s_i+\hat{\theta}_i^{\mathrm{T}}\xi_i(z_i)+\hat{\varepsilon}_i\tanh(s_i\hat{\varepsilon}_i/\tilde{\omega}_i)],\quad(25)$$

$$\dot{\zeta}_i=[k_{i0}(t)s_i+\hat{\theta}_i^{\mathrm{T}}\zeta_i(z_i)+\hat{\varepsilon}_i\tanh(s_i\hat{\varepsilon}_i/\tilde{\omega}_i)]s_i,\quad(26)$$

$$k_{i0}=k_{i1}(t)+\frac{mk_{i2}}{2(1-\bar{\tau}_{\max})\max\{s_i^2,c_{s_i}^2\}}\times\sum_{j=1}^{i}\sum_{k=1}^{m}\int_{t-\tau_{\max}}^{t}\rho_{jk}^2(x_k(\tau))\mathrm{d}\tau,\quad(27)$$

$$k_{i1}=\frac{k}{b_{i0}}\int_0^1\omega b_{i1}(\bar{x}_i^+,\omega s_i+\beta_i)\mathrm{d}\omega,\quad(28)$$

其中 $\bar{\omega}_i,k,k_{i2}$ 为设计正常数.

自适应律

$$\dot{\hat{\theta}}_i=\begin{cases}\eta_i(s_i\xi_i(z_i)-\sigma\hat{\theta}_i), & \|\hat{\theta}_i\|<M_{\theta_i}\text{ 或 }\|\hat{\theta}_i\|=M_{\theta_i},s_i\hat{\theta}_i^{\mathrm{T}}\xi_i(z_i)\leq0;\\ \eta_i\Big(s_i\xi_i(z_i)-\sigma\hat{\theta}_i-s_i\dfrac{\hat{\theta}_i\hat{\theta}_i^{\mathrm{T}}}{\|\hat{\theta}_i\|^2}\xi_i(z_i)\Big), & \|\hat{\theta}_i\|=M_{\theta_i},s_i\hat{\theta}_i^{\mathrm{T}}\xi_i(z_i)>0;\end{cases}\quad(29)$$

$$\dot{\hat{\varepsilon}}_i=\eta_{i1}[s_i\tanh(s_i/\bar{w}_i)-\sigma_{i1}\hat{\varepsilon}_i],\quad(30)$$

其中 $\sigma,\sigma_{i1},\eta_i,\eta_{i1}$ 是正的设计常数.

4 稳定性分析

令 $V_\theta=\frac{1}{2}\hat{\theta}_i^{\mathrm{T}}\hat{\theta}_i$,类似于文献[13]的讨论可知,只要参数 $\hat{\theta}_i(0)\in\Omega_{\theta_i}$,则 $\|\hat{\theta}_i\|<M_{\theta_i},\forall t\geq0$.

定理 2 考虑对象(1),其控制律由式(25)～(28)确定,自适应律由式(29)和(30)确定,并满足假设 1～假设 8,则对于有界初始条件,闭环系统是半全局一致终结有界的.

$$\hat{\theta}_i\in\{\hat{\theta}_i|\ \|\tilde{\theta}_i\|^2\leq2\eta_i\mu_i,\theta_i^*\in\Omega_{\theta_i}\},$$

$$x_i\in\Omega_{ic}=\{x_i|\ \|x_i-x_d\|\leq c_{i0}(1+\|\Lambda_i\|)\|\omega_i(0)\|+[1+$$

$$\frac{(1+\|\Lambda_i\|)c_{i0}}{\lambda_i}\Big]\max\{\sqrt{2\mu_i},c_{s_i}\},\bar{x}_{id}\in\Omega_{id}\Big\}\subset$$

Ω_i.

证明　1) 考虑如下 Lyapunov 函数:

$$V_i(t)=V_{s_i}(t)+V_{U_i}(t)+\frac{1}{2\eta_i}\tilde{\theta}_i^{\mathrm{T}}\tilde{\theta}_i+\frac{1}{2\eta_{i1}}\tilde{\varepsilon}_i^2, \tag{31}$$

则

$$\dot{V}_i(t)=\dot{V}_{s_i}(t)+\dot{V}_{U_i}(t)+\frac{1}{\eta_i}\tilde{\theta}_i^{\mathrm{T}}\dot{\hat{\theta}}_i+\frac{1}{\eta_{i1}}\tilde{\varepsilon}_i\dot{\hat{\varepsilon}}_i\le$$
$$s_iB_i(t)v_i+s_i[\theta_i^{*\mathrm{T}}\xi_i(z_i)+\varepsilon_i^*(z_i)]+\frac{p_i^{*2}}{2}+$$
$$\frac{m}{2(1-\bar{\tau}_{\max})}\Big[1-\frac{s_i^2}{c_{s_i}^2}\Big]\sum_{j=1}^{i}\sum_{k=1}^{m}\rho_{jk}^2(x_k(t))+$$
$$\frac{1}{\eta_i}\tilde{\theta}_i^{\mathrm{T}}\dot{\hat{\theta}}_i+\frac{1}{\eta_{i1}}\tilde{\varepsilon}_i\dot{\hat{\varepsilon}}_i+\frac{H_i^{*2}}{2}. \tag{32}$$

使用控制律(25) ～ (28),自适应律(29)和(30),$0\le|x|-x\tanh(x/\varepsilon)\le 0.2785\varepsilon,\varepsilon>0,x\in R$,并由式(32)可得

$$\dot{V}_i(t)\le$$
$$\Psi_i(t)N(\zeta_i)\dot{\zeta}_i+\dot{\zeta}_i-k_{i1}s_i^2-k_{i2}V_{U_i}+$$
$$\frac{m(k_{i2}\tau_{\max}+1)}{2(1-\bar{\tau}_{\max})}\rho_{\max}+\frac{p_i^{*2}+H_i^{*2}}{2}-$$
$$\sigma_i\tilde{\theta}_i^{\mathrm{T}}\hat{\theta}_i-\sigma_{i1}\tilde{\varepsilon}_i\hat{\varepsilon}_i+0.2785\tilde{\omega}_i. \tag{33}$$

其中

$$\rho_{\max}=\max_{x_i\in\Omega_{c_{s_i}}}\sum_{j=1}^{i}\sum_{k=1}^{m}\rho_{jk}^2(x_k(t)),$$

$$\Psi_i(t)=\frac{b_i(\bar{x}_i)K_i^{\mathrm{T}}(t)\Phi_i(t)}{|b_i(\bar{x}_i)|}.$$

由于下列不等式成立:

$$-\sigma_i\tilde{\theta}_i^{\mathrm{T}}\hat{\theta}_i\le-\frac{\sigma_i\|\tilde{\theta}_i\|^2}{2}+\frac{\sigma_i\|\theta_i^*\|^2}{2}, \tag{34}$$

$$-\sigma_{i1}\tilde{\varepsilon}_i\hat{\varepsilon}_i\le-\frac{\sigma_{i1}\tilde{\varepsilon}_i^2}{2}+\frac{\sigma_{i1}\varepsilon_i^{*2}}{2}. \tag{35}$$

将式(34)和(35)代入(33),可得

$$\dot{V}_i(t)\le$$
$$-kv_{s_i}-k_{i2}V_{U_i}+\frac{m(k_{i2}\tau_{\max}+1)}{2(1-\bar{\tau}_{\max})}\rho_{\max}+$$
$$\Psi_i(t)N(\zeta_i)\dot{\zeta}_i+\dot{\zeta}_i-\frac{\sigma_i\|\tilde{\theta}_i\|^2}{2}-\frac{\sigma_{i1}\tilde{\varepsilon}_i^2}{2}+$$
$$0.2785\tilde{\omega}_i+\frac{\sigma_{i1}\varepsilon_i^{*2}+\sigma_i\|\theta_i^*\|^2+H_i^{*2}+p_i^{*2}}{2}. \tag{36}$$

令

$$\lambda_{i0}=\min(k,k_{i2},\sigma_i\eta_i,\sigma_{i1}\eta_{i1}), \tag{37}$$

$$\mu_{i0}=0.2785\tilde{\omega}_i+\frac{\sigma_{i1}\varepsilon_i^{*2}}{2}+$$
$$\frac{\sigma_i\|\theta_i^*\|}{2}+\frac{p_i^{*2}+H_i^{*2}}{2}, \tag{38}$$

则

$$\dot{V}_i(t)\le$$
$$-\lambda_{i0}V(t)+\mu_{i0}+\frac{m(k_{i2}\tau_{\max}+1)}{2(1-\bar{\tau}_{\max})}\rho_{\max}+$$
$$\Psi_i(t)N(\zeta_i)\dot{\zeta}_i+\dot{\zeta}. \tag{39}$$

式(39)两边同乘以 $e^{\lambda_{i0}t}$,求解可得

$$V_i(t)\le c_{i0}+e^{-\lambda_{i0}t}\int_0^t(\Psi_i(t)N(\zeta_i)\dot{\zeta}_i+\dot{\zeta})e^{\lambda_{i0}\tau}d\tau, \tag{40}$$

其中

$$c_{i0}=\frac{\mu_{i0}+\frac{m(k_{i2}\tau_{\max}+1)}{2(1-\bar{\tau}_{\max})}\rho_{\max}}{\lambda_{i0}}+V_i(0). \tag{41}$$

由引理 1,有 $V_i(t)$,$\zeta_i(t)$,$\int_0^t\Psi_i(\tau)N(\zeta_i)\dot{\zeta}_i d\tau$ 在 $[0,t_f)$ 上有界.因此,$\tilde{\varepsilon}_i$,$\|\tilde{\theta}_i\|$,$|s_i|$ 在 $[0,t_f)$ 上有界.令 C_{ζ_i} 是 $e^{-\lambda_{i0}t}\int_0^t(\Psi_i(\tau)N(\zeta_i)\dot{\zeta}_i+\dot{\zeta})e^{\lambda_{i0}\tau}d\tau$ 在 $[0,\infty)$ 的上界,$\mu_i=c_{i0}+C_{\zeta_i}$,有 $s_i^2\le 2V_i(t)\le 2\mu_i$.由式(12)可知 $s_i^2\le 2V_{s_i}(t)\le 2V_i(t)$.类似地,有 $\{\hat{\theta}_i\,|\,\|\hat{\theta}_i\|^2\le 2\eta_i\mu_i,\theta_i^*\in\Omega_{\theta_i}\}$.

2) 定义 $\omega_i=[e_{i1},e_{i2},\cdots,e_{i,n_i-1}]^{\mathrm{T}}\in R^{n_i-1}$,由式(6)可知存在 $\dot{\omega}_i=A_{s_i}\omega_i+b_{s_i}s_i$.其中:$s_i=[\Lambda_i^{\mathrm{T}},1]e_i$,$\Lambda_i=[\lambda_{i1},\lambda_{i2},\cdots,\lambda_{i,n_i-1}]^{\mathrm{T}}$,$b_{s_i}=[0,\cdots,0,1]^{\mathrm{T}}\in R^{n_i-1}$,$A_{s_i}$ 是一个稳定的矩阵.存在一个正常数 c_{i0},满足 $\|e^{A_{s_i}t}\|\le c_{i0}e^{-\lambda_i t}$,$i=1,2,\cdots,m$.

求解线性方程 $\dot{\omega}_i=A_{s_i}\omega_i+b_{s_i}s_i$,得

$$\omega_i(t)=e^{A_{si}(t)}\omega_i(0)+\int_0^t e^{A_{s_i}(t-\tau)}b_{s_i}s_i(\tau)d\tau.$$

因此可得

$$\|\omega_i(t)\|\le$$
$$c_{i0}\|\omega_{i0}\|e^{-\lambda_i t}+c_{i0}\int_0^t e^{-\lambda_i(t-\tau)}|s_i(\tau)|d\tau.$$

令 $\bar{\mu}_i=\max\{\sqrt{2\mu_i},c_{s_i}\}$,所以

$$\|\omega_i(t)\|\le c_{i0}\|\omega_i(0)\|+c_{i0}\bar{\mu}_i/\lambda_i. \tag{42}$$

注意到 $s_i=\Lambda_i^{\mathrm{T}}\omega_i+e_{in_i}$,$e_i=[\omega_i^{\mathrm{T}},e_{in_i}]^{\mathrm{T}}$,于是有

$$\|e_i\|\le\|\omega_i\|+|e_{in_i}|\le$$
$$(1+\|\Lambda_i\|)\|\omega_i\|+|s_i|. \tag{43}$$

将式(42)代入(43),可得

$$\|e_i\|\le c_{i0}(1+\|\Lambda_i\|)\|\omega_i(0)\|+$$
$$\Big[1+\frac{(1+\|\Lambda_i\|)c_{i0}}{\lambda_i}\Big]\bar{\mu}_i. \tag{44}$$

由于 $x=e+x_d$ 以及假设 5,有

$$\|x_i\|\le\|e_i\|+\|x_{id}\|\le$$
$$c_{i0}(1+\|\Lambda_i\|)\|\omega_i(0)\|+\|x_{id}\|+$$
$$\Big[1+\frac{(1+\|\Lambda_i\|)c_{i0}}{\lambda_i}\Big]\max\{\sqrt{2\mu_i},c_{s_i}\}\in L_\infty.$$

由此可知,闭环系统是半全局一致有界的. □

5 仿真结果

为了验证设计方法的有效性,考虑如下非线性系统,其动态方程如下:

$$\begin{aligned}
\dot{x}_{11}(t) &= x_{12}(t),\\
\dot{x}_{12}(t) &= x_{21}(t) - 0.3\sin(x_{21}(t)) + 0.1x_{11}^2(t-\tau_1(t)) + (2 - \sin^2(x_{11}(t)))u_1(t) + \sin(x_{21}),\\
\dot{x}_{21}(t) &= x_{22}(t),\\
\dot{x}_{22}(t) &= x_{11}^2 u_1(t) + (x_{22}^2(t) + x_{11}(t) + 0.5\cos(x_{21}(t)))u_1^2(t) + 0.2x_{22}(t-\tau_2(t))\sin(x_{21}(t-\tau_2(t))) + (3+\sin(x_{22}(t)))u_2(t) + 0.5\sin(x_{22}),\\
y_1(t) &= x_{11}(t),\ y_2(t) = x_{21}(t),
\end{aligned}$$

其中 u_1 和 u_2 是死区输出. 控制目标是设计控制律 v_1 和 v_2,使得系统输出 y_1 和 y_2 的跟踪轨迹为 $y_{1d}(t) = 0.5[\sin(t)+\sin(0.5t)]$, $y_{2d}(t) = [\sin(0.5t) + 0.5\sin(1.5t)]$. 仿真中选取设计参数 $\lambda_{11} = 1.5$, $\lambda_{21} = 2$, $k = 0.02$, $k_{12} = k_{22} = 0.05$, $\eta_1 = 0.1$, $\eta_2 = \eta_{11} = \eta_{12} = 0.1$, $\sigma_1 = \sigma_2 = 0.01$, $\sigma_{11} = 0.01$, $\sigma_{21} = 0.01$, $\tilde{\omega}_1 = \tilde{\omega}_2 = 0.2$, $\zeta_1(0) = 0.8$, $\zeta_2(0) = 0.5$. 死区参数 $k_{1l} = 0.5$, $k_{1r} = 1.5$, $k_{2l} = 1.5$, $k_{2r} = 2.5$, $b_{1l} = -0.5$, $k_{2l} = -2.5$, $k_{2r} = 2$, 初值条件为 $x_{11}(0) = x_{12}(0) = 0$, $x_{21}(0) = x_{22} = 0$, $M_{\theta_i} = 4$, 时滞 $\tau_1(t) = \tau_2(t) = 1 + 0.5\sin(t)$, $\tau_{\max} = 2$, $\bar{\tau}_{\max} = 0.6$. $\theta_1(0)$ 和 $\theta_2(0)$ 在区间 $[-1,1]$ 上随机选取, $\varepsilon_1(0) = \varepsilon_2(0) = 0.5$, 仿真结果如图 1 和图 2 所示. 仿真结果表明,本文提出的控制方案具有良好的跟踪性能.

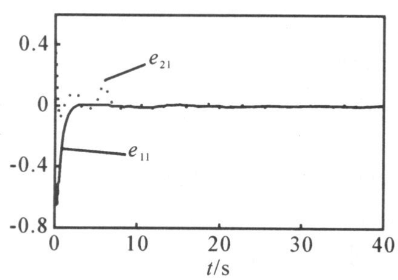

图 1 跟踪误差曲线

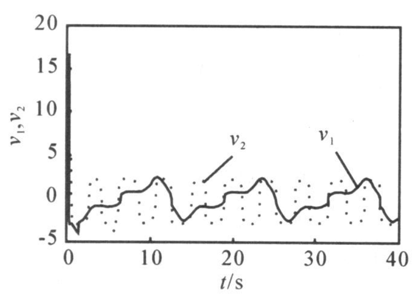

图 2 控制信号

6 结 论

本文针对一类具有未知死区和控制增益符号不确定的多输入多输出非线性时滞系统,基于滑模控制原理和 Nussbaum 函数的性质,提出一种稳定自适应控制方案. 该方案放宽了对函数控制增益上界为未知常数的假设,并通过使用 Lyapunov-Krasovskii 泛函抵消了因未知时变时滞带来的系统不确定性. 进一步引入连续函数,避免了逼近函数可能的不连续性,并通过使用积分型 Lyapunov 函数,避免了控制器的奇异性问题. 理论分析证明,闭环系统是半全局一致终结有界的.

参考文献(References)

[1] Tao G, Kokotovic P V. Adaptive sliding control of plants with unknown dead-zone[J]. IEEE Trans on Automatic Control, 1994, 39(1): 59-68.

[2] Tao G, Kokotovic P V. Discrete-time adaptive control of systems with unknown dead-zone[J]. Int J of Control, 1995, 61(1): 1-17.

[3] Cho H Y, Bai E W. Convergence results for an adaptive dead zone inverse[J]. Int J of Adaptive Control and Signal Processing, 1998, 12(5): 451-466.

[4] Wang X S, Hong H, Su C Y. Model reference adaptive control of continuous time systems with an unknown dead-zone [J]. IEE Proc of Control Theory Applications, 2003, 150(3): 261-266.

[5] Wang X S, Hong H, Su C Y. Robust adaptive control a class of nonlinear systems with an unknown dead-zone [J]. Automatica, 2004, 40(3): 407-413.

[6] Ge S S, Hong F, Lee T H. Adaptive neural control of nonlinear time-delay systems with unknown virtual control coefficients[J]. IEEE Trans on Systems, Man and Cybernetics, 2004, 34(1): 499-516.

[7] Shyu K K, Liu W J, Hsu K C. Design of large-scale time-delayed system with dead-zone via variable structure control[J]. Automatica, 2005, 41(7): 1239-1246.

[8] Ge S S, Hong F, Lee T H. Adaptive neural control of nonlinear systems with unknown time delays[J]. IEEE Trans on Automatic Control, 2003, 48(11): 2004-2010.

[9] Ge S S, Hong F ,Lee T H. Robust adaptive control of nonlinear systems with unknown time delays [J]. Automatic control, 2005, 41(7): 1181-1190.

[10] Hale J. Theory of functional differential equations [M]. New York: Springer, 1997.

[11] Zhang T P, Ge S S. Adaptive neural control of MIMO nonlinear time-varying delay systems with unknown dead-zone and gain signs [J]. Automatica, 2007, 43 (6): 1021-1033.

(下转第 1162 页)

10]，$\beta \in [0,1.0]$，$\varepsilon \in [0,1.0]$. 其中 K_p，K_i，K_d 分别是比例、积分、微分的增益系数. 对于对象 B，其控制参数设置如下：$K_p \in [0,15]$，$K_i \in [0,10]$，$K_d \in [0,5]$，$\lambda \in [1,20]$，$\alpha \in [0,2]$，$\beta \in [0,0.5]$，$\varepsilon_1 \in [0,1.0]$，$\varepsilon_2 \in [0,0.5]$. 优化控制参数如表 1 和 2 所示，对象 A 和 B 的比较控制效果如图 3 和 4 所示. 与传统优化 PID 控制算法相比，NOIC 能够更快速稳定地消除控制偏差. 而且对于控制对象 A 而言，传统 PID 控制算法的控制参数即使得到优化，仍然难以稳定控制. 从仿真结果可以看出，NOIC 的控制性能均优于传统 PID 控制算法；且 NOIC 在没有积分作用的情况下仍能够消除控制偏差，其主要原因是算法的非线性和控制偏差的适度提呈.

表 1　传统 PID 控制方法的优化控制参数

控制参数		K_p	K_i	K_d
对象	A	0.0374	0.1043	4.9271
	B	0.1388	0.1099	0.4728

表 2　NOIC 的优化控制参数

控制参数		λ	K_p	α	β	ε_1	ε_2
对象	A	3.7406	0.9347	3.0658	0.2314	0.09078	0.0903
	B	3.1060	3.9622	1.1061	0.1213	0.2161	0.0079

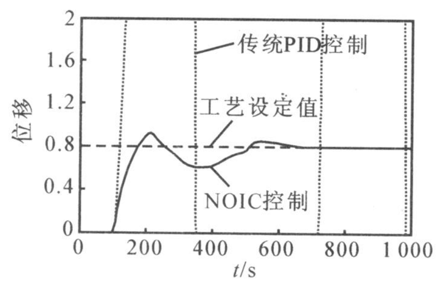

图 3　对象 A 的控制效果比较

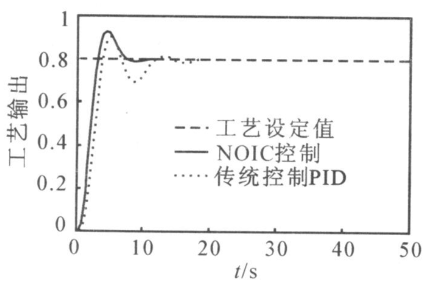

图 4　对象 B 的控制效果比较

5　结　　论

本文基于 NEI 的整体调节机制，提出一种非线性优化智能控制器. PU 首先根据免疫提呈机制对控制偏差进行动态处理；ACU 通过调整控制实体的数量来消除控制偏差；MCU 用来调整 PU 和 ACU 的控制作用；OU 和 IU 基于 GA 算法优化 PU 和 ACU 的参数. 为了检验 NOIC 的控制性能，最后选择 2 个控制对象进行计算机仿真. 仿真结果表明，相对于传统的 PID 控制，NOIC 具有较好的控制性能.

参考文献(References)

[1] Yao X, Liu Y. Making use of population information in evolutionary artificial neural networks[J]. IEEE Trans on Systems, Man and Cybernetics, 1998, 28(3): 417-425.

[2] 刘宝，丁永生. 一种基于免疫存储记忆的智能控制器的设计与实现[J]. 控制与决策, 2005, 20(10): 1169-1172.
(Liu B, Ding Y S. Design and implementation of an intelligent controller based on immune store-memory [J]. Control and Decision, 2005, 20(10): 1169-1172.)

[3] Farhy L S. Modeling of oscillations of endocrine networks with feedback[J]. Methods Enzymol, 2004, 384(1): 54-81.

[4] Vargas P, Moioil R, Castro L N D, et al. Artificial homeostatic system: A novel approach[J]. Lecture Notes in Artificial Intelligence, 2005, 3630: 754-764.

[5] Besedovsky H, Sorkin E. Network of immune-neuroendocrine interactions [J]. Clinical and Experimental Immunology, 1977, 27(1): 1-12.

[6] Brazzini B, Ghersetich I, Hercogova J, et al. The neuro-immuno-cutaneousendocrine network: Relationship between mind and skin[J]. Dermatologic Therapy, 2003, 16(2): 123-131.

[7] Kim D H. PID controller tuning of a boiler control system using immune algorithm typed neural network [C]. Proc of Computational Science-ICCS 2004: 4th Int Conf. Krakow, 2004: 695-698.

[8] Liu B, Ren L H, Ding Y S. A novel intelligent controller based on modulation of neuroendocrine system [C]. Proc of the 2nd Int Symposium on Neural Networks. New York: Springer-Verlag, 2005: 119-124.

(上接第 1158 页)

[12] Nussbaum R D. Some remarks on the conjecture in parameter adaptive control[J]. Systems and Control Letters, 1983, 3(3): 243-246.

[13] Zhang T P, Yi Y. Adaptive fuzzy control for a class of MIMO nonlinear systems with unknown dead-zones [J]. Acta Automatica Sinica, 2007, 33(1): 96-100.