控制增益符号已知的 MIMO 非线性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： 针对一类具有死区模型并且控制增益符号已知的不确定多输入多输出非线性时滞系统，基于滑模控制原理提出了一种稳定的自适应神经网络控制方案。该方案通过使用 Lyapunov－Krasovskii 泛函抵消了因未知时变时滞带来的系统不确定性。通过利用积分型李亚普诺夫函数，并且构造逼近连续函数，闭环系统证明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
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Adaptive Control of MIMO Nonlinear Time Delay Systems with Known Control Gain Signs

QIAN Houbin[a,b]， ZHANG Tianping[a]
（Yangzhou University，a. College of Information Engineering；
b. College of Journalism & Communication，Yangzhou 225009，China）

Abstract： A design scheme of adaptive neural controller is proposed for a class of uncertain MIMO nonlinear time-varying delay system with unknown nonlinear dead-zones and known function control gain. The design is based on the principle of sliding mode control. The unknown time-varying delay uncertainties are compensated by using appropriate Lyapunov-Krasovskii Functionals in the design. By utilizing the integral Lyapunov Function and constructing approximated continuous functions，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

0 引言

在许多工业过程控制系统中，死区非线性是系统中常见的一种非线性环节。文献[1]通过简化死区模型使控制律的设计更为简单，然而只讨论了控制增益为常数的情况。文献[2]考虑了一类斜率相等的未知死区和三角结构的 MIMO 非线性系统的模糊自适应控制问题。在各类工业系统中，时滞现象也是普遍存在的。如传送系统，化工过程系统等都是典型的时滞系统。时滞的存在往往是系统不稳定和系统性能变差的根源，所以时滞系统的稳定性问题一直是人们感兴趣的课题之一。文献[3]对具有三角块结构的 MIMO 非线性时滞系统，提出一种新的自适应控制方案。然而，文中对虚拟控制 α_{i-1} 利用复合函数求导规则确定建模变量时值得商榷。文献[4]中只讨论了控制增益为常数且死区模型的倾斜度相等的情况。文献[5]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，然而遗憾的是该条件往往因为先验知识不足而无法达到。文献[6－7]分别针对具有未知时滞和虚拟控制系数为未知常数的非线性系统和具有三角块结构的 MIMO 非线性时滞系统，利用神经网络逼近并补偿系统中未知函数，通过使用文献[8]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。文献[9]针对一类具有未知死区和控制增益符号未知的 MIMO 非线性

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作者简介： 钱厚斌（1973 —），男，江苏姜堰人，助理研究员，硕士，研究方向为自适应控制、神经网络控制等。E－mail：qhb7311@sina.com

时变时滞系统,提出了一种稳定的自适应神经网络控制方案。文献[10]考虑了具有时变输入时滞不确定系统的鲁棒镇定问题,以LMI的形式给出了时滞相关的鲁棒可镇定充分条件及相应的无记忆鲁棒控制器设计方法。

本文考虑了一类具有未知死区和控制增益符号已知的MIMO非线性时变时滞系统的自适应控制问题,通过引入积分型李亚普诺夫函数和变结构控制策略,提出一种稳定的自适应神经网络控制方案。文中构造的连续逼近函数,能够有效地避免在文献[4,6,9,11]中设计控制器时出现的奇异性问题,新的方案在工程实际应用当中能够更好适应对控制器的严格要求。

1 问题的描述及基本假设

考虑下面一类多输入多输出的时滞非线性系统:

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

定义输入为 $v_i(t)$,输出为 $u_i(t)$ 的死区模型描述如下:

$$u_i(t)=D_i(v_i(t))=\begin{cases}g_{ir}(v_i(t)), & v_i(t)\geqslant b_{ir}\\ 0, & b_{il}<v_i(t)<b_{ir}\\ g_{il}(v_i(t)), & v_i(t)\leqslant b_{il}\end{cases} \tag{2}$$

其中:$\boldsymbol{x}$ 是状态向量,且 $\boldsymbol{x}=[x_1^{\mathrm{T}},x_2^{\mathrm{T}},\cdots,x_m^{\mathrm{T}}]^{\mathrm{T}}\in R^n$,$\boldsymbol{x}_i=[x_{i1},x_{i2},\cdots,x_{in_i}]^{\mathrm{T}}$,$i=1,\cdots,m$,$n=\sum\limits_{i=1}^{m}n_i$;$g_{ir}(v_i)$,$g_{il}(v_i)$ 是未知光滑非线性函数;y_i 是第 i 个子系统的输出;$f_1(x),f_2(x,u_1),\cdots,f_m(x,u_1,\cdots,u_{m-1}),g_{i,\tau}(x_1(t-\tau_1(t)),\cdots,x_m(t-\tau_m(t)))$ 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,$\bar{\boldsymbol{x}}_i=[\boldsymbol{x}_1^{\mathrm{T}},\boldsymbol{x}_2^{\mathrm{T}},\cdots,\boldsymbol{x}_i^{\mathrm{T}}]^{\mathrm{T}}$;$\tau_1(t),\cdots,\tau_m(t)$ 是未知时变时滞,$\phi_1(t),\cdots,\phi_m(t)$ 为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。$u_i\in\mathbf{R}$ 是第 i 个死区的输出(是第 i 个系统的输入),$v_i(t)\in\mathbf{R}$ 是第 i 个死区的输入,b_{il},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。

输入为 $v_i(t)$ 不对称非线性死区如图1所示。

为设计稳定的自适应神经网络控制,作如下假设:

1) 死区输出 $u_1,\cdots,u_m$ 是不可量测的;

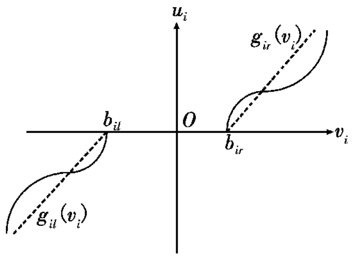

图1 输入为 $v_i(t)$ 不对称非线性死区

Fig.1 Nonsymmetric nonlinear dead-zone model

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

3) $g_{il}(v_i)$,$g_{ir}(v_i)$ 是光滑的,并且存在未知的正常数 β_{i0},k_{il1},k_{ir1} 满足:

$$0<\beta_{i0}\leqslant g_{il}'(v_i)\leqslant k_{il1},\ \forall v_i\in(-\infty,b_{il}] \tag{3}$$

$$0<\beta_{i0}\leqslant g_{ir}'(v_i)\leqslant k_{ir1},\ \forall v_i\in[b_{ir},+\infty) \tag{4}$$

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,参照文献[10],死区可以重新定义为

$$u_i(t)=D_i(v_i)=\boldsymbol{K}_i^{\mathrm{T}}(t)\boldsymbol{\Phi}_i(t)v_i+d_i(v_i) \tag{5}$$

其中:$\boldsymbol{\Phi}_i(t)=[\varphi_{ir}(t),\varphi_{il}(t)]^{\mathrm{T}}$,

$$\boldsymbol{k}_i(t)=[g'_{ir}(\xi_{ir}(v_i(t))),g'_{il}(\xi_{il}(v_i(t)))]^{\mathrm{T}},$$

$$\varphi_{ir}(t)=\begin{cases}1, & v_i(t)>b_{il}\\ 0, & v_i(t)\leqslant b_{il}\end{cases} \tag{6}$$

$$\varphi_{il}(t)=\begin{cases}1, & v_i(t)<b_{ir}\\ 0, & v_i(t)\geqslant b_{ir}\end{cases} \tag{7}$$

$$d_i(v_i)=\begin{cases}-g'_{ir}(\xi_{ir}(v_i))b_{ir}, & v_i\geqslant b_{ir}\\ -[g'_{il}(\xi_{il}(v_i))+g'_{ir}(\xi_{ir}(v_i))]v_i, & b_{il}<v_i<b_{ir}\\ -g'_{il}(\xi_{il}(v_i))b_{il}, & v_i\leqslant b_{il}\end{cases} \tag{8}$$

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

控制目标是要求系统输出 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:

$\boldsymbol{x}_{id}=[y_{id},\cdots,y_{id}^{(n_i-1)}]^{\mathrm{T}}$,

$\boldsymbol{e}_i=\boldsymbol{x}_i-\boldsymbol{x}_{id}=[e_{i1},e_{i2},\cdots,e_{in_i}]^{\mathrm{T}}$,

滤波跟踪误差:

$$s_i=\left(\frac{\mathrm{d}}{\mathrm{d}t}+\lambda_i\right)^{n_i-1}e_{i1}=\sum_{j=1}^{n_i-1}\lambda_{ij}e_{ij}+e_{in_i} \tag{9}$$

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

4) 光滑函数 $b_i(\bar{x}_i)$ 符号已知,存在正常数 b_{i0},及函数 $b_{i1}(\bar{x}_i)$,满足 $0<b_{i0}\leqslant b_i(\bar{x}_i)\leqslant b_{i1}(\bar{x}_i)$,$\forall\bar{x}_i\in R^{\bar{n}_i}$,

$\bar{n}_j = \sum_{j=1}^{i} n_j, i = 1,\cdots,m$。

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

6) $|g_{i,\tau}(x_1(t-\tau_1(t)),\cdots,x_m(t-\tau_m(t)))| \leqslant \sum_{k=1}^{m}\rho_{ik} \cdot (x_k(t-\tau_k(t)), \rho_{ik}(x_k(t))$ 为已知正连续函数，$i = 1,\cdots,m$。

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

8) $|\Delta_i(x,t)| \leqslant H^* N(\bar{x}_i)$，$N(\bar{x}_i)$是已知非负连续函数，$H^*$是未知正常数。

定义：$(\tilde{\bullet}) = (\hat{\bullet}) - (\bullet)^*$

本文中，"$\bullet$"是通用公式，在自适应律和控制律中的相关参数遵循此运算规则。

2　自适应神经网络控制器的设计稳定性分析

由式(1)、式(5)、式(9)可得：

$$\dot{s}_i = f_i(x,u_1,\cdots,u_{i-1}) + \gamma_i + b_i(\bar{x}_i)\boldsymbol{K}_i^{\mathrm{T}}\boldsymbol{\Phi}_i(t)v_i(t) + g_{i,\tau} \cdot (x_1(t-\tau_1(t)),\cdots,x_m(t-\tau_m(t))) + b_i(\bar{x}_i) \cdot d_i(v_i(t)) + \Delta_{i,n_i}(x,t) \tag{10}$$

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

定义光滑函数如下：

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

其中：$\alpha_i(\bar{x}_i) = b_{i1}(\bar{x}_i)/b_i(\bar{x}_i)$，$\beta_i = y_{id}^{(n_i-1)} - \sum_{j=1}^{n_i-1}\lambda_{ij}e_{i,j}$，$\bar{\boldsymbol{x}}_i^+ = [\boldsymbol{x}_1^{\mathrm{T}}, \boldsymbol{x}_2^{\mathrm{T}},\cdots,\boldsymbol{x}_{i-1}^{\mathrm{T}}, x_{i1},\cdots,x_{i,n_i-1}]^{\mathrm{T}}$。

因为$0 < b_{i0} < b_i(\bar{\boldsymbol{x}}_i) < b_{i1}(\bar{\boldsymbol{x}}_i)$，由积分中值定理可知，$\exists\lambda_s \in (0,1)$，使得：

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

所以有 $V_{s_i} \geqslant \frac{s_i^2}{2} > 0$，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可知：

$$\begin{aligned}\dot{V}_{s_i} = {} & s_i\alpha_i(\bar{\boldsymbol{x}}_i)\dot{s}_i + \sum_{j=1}^{i-1} g_{j,\tau}(x_1(t-\tau_1(t)),\cdots,x_m(t-\tau_m(t)))\int_0^{s_i}\sigma\frac{\partial\alpha_i(\bar{\boldsymbol{x}}_i^+,\sigma+\beta_i)}{\partial x_{jn_j}}\mathrm{d}\sigma + \int_0^{s_i}\sigma \cdot \\ & \left\{\sum_{j=1}^{i}\sum_{k=1}^{n_j-1}\frac{\partial\alpha_i(\bar{\boldsymbol{x}}_i^+,\sigma+\beta_i)}{\partial x_{jk}} \times x_{j,k+1} + \sum_{j=1}^{i-1}\frac{\partial\alpha_i(\bar{\boldsymbol{x}}_i^+,\sigma+\beta_i)}{\partial x_{jn_j}} \cdot \right. \\ & \left.\left[f_j(x,u_1,\ldots,u_{j-1}) + b_j(\bar{x}_j)D_j(v_j) + \Delta_{i,n_i}(x,t)\right]\right\}\mathrm{d}\sigma + \\ & \int_0^{s_i}\frac{\sigma a_i(\bar{\boldsymbol{x}}_i^+,\sigma+\beta_i)}{\partial\beta_i}\dot{\beta}_i\mathrm{d}\sigma\end{aligned} \tag{13}$$

因为 $\frac{\partial\alpha_i(\bar{\boldsymbol{x}}_i^+,\sigma+\beta_i)}{\partial\beta_i} = \frac{\partial\alpha_i(\bar{\boldsymbol{x}}_i^+,\sigma+\beta_i)}{\partial\sigma}$ 而且 $\dot{\beta}_i = -\gamma_i$，所以有：

$$\int_0^{s_i}\frac{\partial\alpha_i(\bar{\boldsymbol{x}}_i^+,\sigma+\beta_i)}{\partial\beta_i}\dot{\beta}_i\mathrm{d}\sigma = -\gamma_i\int_0^{s_i}\sigma\frac{\partial\alpha_i(\bar{\boldsymbol{x}}_i^+,\sigma+\beta_i)}{\partial\sigma}\mathrm{d}\sigma = -\gamma_i s_i\alpha_i(\bar{\boldsymbol{x}}_i) + \gamma_i\int_0^{s_i}\alpha_i(\bar{\boldsymbol{x}}_i^+,\sigma+\beta_i)\mathrm{d}\sigma \tag{14}$$

将(14)式代入(13)式中，应用(10)式可得：

$$\begin{aligned}\dot{V}_{s_i} \leqslant {} & s_i b_{i1}(\bar{\boldsymbol{x}}_i)\boldsymbol{K}_i^{\mathrm{T}}(t)\boldsymbol{\Phi}_i(t)v_i + s_iQ_i(z_i) + s_i\alpha_i(\bar{\boldsymbol{x}}_i)g_{i,\tau} \cdot \\ & (x_1(t-\tau_1(t)),\cdots,x_m(t-\tau_m(t))) + |s_i|b_{i1}p_i^* + \\ & \sum_{j=1}^{i-1}g_{j,\tau}(x_1(t-\tau_1(t)),\cdots,x_m(t-\tau_m(t)))\int_0^{s_i}\sigma \cdot \\ & \sum_{i=1}^{n-1}\frac{\partial\alpha_i(\bar{\boldsymbol{x}}_i,\sigma+\beta_i)}{\partial x_{jn_j}}\mathrm{d}\sigma + |s_i|\alpha_i(\bar{\boldsymbol{x}}_i)H_i^*N(\bar{\boldsymbol{x}}_i)\end{aligned} \tag{15}$$

其中：

$$\begin{aligned}Q_i(z_i) = {} & f_i(x,u_1,\cdots,u_{i-1})a_i(\bar{\boldsymbol{x}}_i) + \int_0^1\Big\{\theta \cdot \\ & \sum_{j=1}^{i}\sum_{k=1}^{n_{i-1}}\frac{\partial\alpha_i(\bar{\boldsymbol{x}}_i,\theta s_i+\beta_i)}{\partial x_{jk}} \times x_{j,k+1} + \\ & \sum_{j=1}^{i-1}\frac{\partial\alpha_i(\bar{\boldsymbol{x}}_i,\theta s_i+\beta_i)}{\partial x_{jn_j}}\theta\Big[f_j(x,u_1,\cdots,u_{j-1}) + b_j(\bar{\boldsymbol{x}}_j) \cdot \\ & D_j(v_j) + \Delta_{i,n_i}(x,t)\Big] + \gamma_i\alpha_i(\bar{\boldsymbol{x}}_i^+,\theta s_i+\beta_i)\Big\}\mathrm{d}\theta\end{aligned} \tag{16}$$

$$z_i = [\boldsymbol{x}^{\mathrm{T}}, s_i, \gamma_i, \beta_i, v_1,\cdots,v_{i-1}]^{\mathrm{T}} = [z_{i1}, z_{i2},\cdots,z_{ip_i}]^{\mathrm{T}}, \quad p_i = n+i+2。 \tag{17}$$

利用假设(6)及 Young's 不等式，有：

$$\begin{aligned}& \sum_{j=1}^{i-1}g_{j,\tau}\Big(x_1(t-\tau_1(t)),\cdots,x_m(t-\tau_m(t))\Big)\int_0^{s_i}\sigma \cdot \\ & \sum_{i=1}^{n-1}\frac{\partial\alpha_i(\bar{\boldsymbol{x}}_i,\sigma+\beta_i)}{\partial x_{jn_j}}\mathrm{d}\sigma \leqslant \frac{m}{2}\sum_{j=1}^{i-1}\sum_{k=1}^{m}\rho_{jk}^2(x_k(t-\tau_k(t))) + \\ & \frac{s_i^4}{2}\sum_{j=1}^{i-1}\left(\int_0^1\theta\frac{\partial\alpha_i(\bar{\boldsymbol{x}}_i^+,\theta s_i+\beta_i)}{\partial x_{jn_j}}\mathrm{d}\theta\right)^2\end{aligned} \tag{18}$$

$$s_ig_{i,\tau}(x_1(t-\tau_1(t)),\cdots,x_m(t-\tau_m(t)))\alpha_i(\bar{\boldsymbol{x}}_i) \leqslant \frac{s_i^2\alpha_i^2(\bar{\boldsymbol{x}}_i)}{2} + \frac{m}{2}\sum_{k=1}^{m}\rho_{ik}^2(x_k(t-\tau_k(t)))。 \tag{19}$$

将(18)式、(19)式代入到(15)式，得：

$$\begin{aligned}\dot{V}_{s_i} \leqslant {} & s_ib_{i1}(\bar{\boldsymbol{x}}_i)\boldsymbol{K}_i^{\mathrm{T}}(t)\boldsymbol{\Phi}_i(t)v_i + s_iQ_i(z_i) + \\ & \frac{s_i^2\alpha_i^2(\bar{\boldsymbol{x}}_i) + s_i^2\alpha_i^2(\bar{\boldsymbol{x}}_i)N^2(\bar{\boldsymbol{x}}_i)}{2} + \frac{m}{2}\sum_{j=1}^{i}\sum_{k=1}^{m}\rho_{jk}^2(x_k(t- \\ & \tau_k(t))) + \frac{s_i^2b_{i1}^2}{2} + \frac{s_i^4}{2}\sum_{j=1}^{i-1}\left(\int_0^1\theta\frac{\partial\alpha_i(\bar{\boldsymbol{x}}_i^+,\theta s_i+\beta_i)}{\partial x_{jn_j}}\mathrm{d}\theta\right)^2 + \\ & \frac{p_i^{*2} + H_i^{*2}}{2}\end{aligned} \tag{20}$$

为克服设计未知时滞 $\tau_1(t), \tau_2(t),\cdots,\tau_m(t)$，定义 Lyapunov-Krasovskii 泛函：

$$V_{u_i}(t)=\frac{m}{2(1-\bar{\tau}_{\max})}\sum_{j=1}^{i}\sum_{k=1}^{m}\int_{t-\tau_k(t)}^{t}\rho_{jk}^2(x_k(\tau))\mathrm{d}\tau \quad (21)$$

对(21)式求导,可得:

$$\dot{V}_{u_i}(t)=\frac{m}{2(1-\bar{\tau}_{\max})}\Big[\sum_{j=1}^{i}\sum_{k=1}^{m}\rho_{jk}^2(x_k(\tau))-\sum_{j=1}^{i}\sum_{k=1}^{m}\rho_{jk}^2(x_k(t-\tau_k(t)))(1-\dot{\tau}_k(t))\Big] \quad (22)$$

则:

$$\dot{V}_{s_i}+\dot{V}_{u_i}(t)\leqslant s_i b_{i1}(\bar{\boldsymbol{x}}_i)\boldsymbol{K}_i^{\mathrm{T}}(t)\boldsymbol{\Phi}_i(t)v_i+s_iQ_i(z_i)+\frac{s_i^2\alpha_i^2(\bar{\boldsymbol{x}}_i)+s_i^2\alpha_i^2(\bar{\boldsymbol{x}}_i)N^2(\bar{\boldsymbol{x}}_i)}{2}+\frac{m}{2}\sum_{j=1}^{i}\sum_{k=1}^{m}\rho_{jk}^2(x_k(t-\tau_k(t)))+\frac{s_i^2b_{il}^2}{2}+\frac{s_i^4}{2}\sum_{j=1}^{i-1}\left(\int_0^1\theta\frac{\partial\alpha_i(\bar{\boldsymbol{x}}_i^+,\theta s_i+\beta_i)}{\partial x_{jn_j}}\mathrm{d}\theta\right)^2+\frac{p_i^{*2}+H_i^{*2}}{2}+\frac{m}{2(1-\bar{\tau}_{\max})}\Big[\sum_{j=1}^{i}\sum_{k=1}^{m}\rho_{jk}^2(x_k(t))-\sum_{j=1}^{i}\sum_{k=1}^{m}\rho_{jk}^2(x_k(t-\tau_k(t)))(1-\dot{\tau}_k(t))\Big]\leqslant s_ib_{i1}(\bar{\boldsymbol{x}}_i)\cdot\boldsymbol{K}_i^{\mathrm{T}}(t)\boldsymbol{\Phi}_i(t)v_i+s_ih_i(z_i)+\frac{p_i^{*2}+H_i^{*2}}{2}+\frac{m}{2(1-\bar{\tau}_{\max})}\Big[1-\frac{s_i^2}{c_{s_i}^2}\Big]\sum_{j=1}^{i}\sum_{k=1}^{m}\rho_{jk}^2(x_k(t)) \quad (23)$$

其中:c_{s_i}是设计正常数,

$$h_i(z_i)=Q_i(z_i)+\frac{s_i\alpha_i^2(\bar{\boldsymbol{x}}_i)+s_i\alpha_i^2(\bar{\boldsymbol{x}}_i)N^2(\bar{\boldsymbol{x}}_i)}{2}+\frac{s_ib_{il}^2}{2}+\frac{s_i^3}{2}\sum_{j=1}^{i-1}\left(\int_0^1\theta\frac{\partial\alpha_i(\bar{\boldsymbol{x}}_i^+,\theta s_i+\beta_i)}{\partial x_{jn_j}}\mathrm{d}\theta\right)^2+\frac{ms_i}{2(1-\bar{\tau}_{\max})c_{s_i}^2}\sum_{j=1}^{i}\sum_{k=1}^{m}\rho_{jk}^2(x_k(t)) \quad (24)$$

定义紧集:

$$\boldsymbol{\Omega}_{z_i}=\Big\{[\boldsymbol{x}^{\mathrm{T}},s_i,\gamma_i,\beta_i,v_1,\cdots,v_{i-1}]^{\mathrm{T}}\,|\,x_j\in\boldsymbol{\Omega}_j,j=1,\cdots,m,\ \bar{\boldsymbol{x}}_{kd}\in\boldsymbol{\Omega}_{kd},k=1,\cdots,i\Big\} \quad (25)$$

$$\boldsymbol{\Omega}_{c_i}=\Big\{x\,\Big|\,|s_i|\leqslant c_{s_i},\bar{\boldsymbol{x}}_{kd}\in\boldsymbol{\Omega}_{kd},k=1,\cdots,i\Big\} \quad (26)$$

其中:$\boldsymbol{\Omega}_j\in R^{n_j}$是一个足够大的紧集。

设$h_i(z_i,\boldsymbol{\theta}_i)$是径向基神经网络在$\boldsymbol{\Omega}_{z_i}$上对$h_i(z_i)$函数的逼近。设$h_i(z_i,\theta_i)$是径向基函数神经网络在闭区域$\boldsymbol{\Omega}_{z_i}$上对$h_i(z_i)$的逼近,即$h_i(z_i,\boldsymbol{\theta}_i)=\boldsymbol{\theta}_i^{\mathrm{T}}\boldsymbol{\xi}_i(z_i)$,其中$\boldsymbol{\theta}_i=(\theta_{i1},\cdots,\theta_{iN_i})^{\mathrm{T}}$是连接权向量,径向基向量为$\boldsymbol{\xi}_i(z_i)=(\xi_{i1}(z_i),\cdots,\xi_{iN_i}(z_i))^{\mathrm{T}}$,基函数为$\xi_{il}(z_i)=\exp\left[-\frac{\sum_{j=1}^{p_i}(z_{ij}-a_{ij}^l)^2}{(b_i^l)^2}\right]$,$l=1,\cdots,N_i$,其中:$b_i^l>0$,$a_{ij}^l\in\mathbf{R}$,$j=1,\cdots,i$。令:

$$\boldsymbol{\Omega}_{\theta_i}=\{\theta_i:\|\theta_i\|\leqslant M_{\theta_i}\},\ \theta_i^*=\arg\min_{\theta_i\in\boldsymbol{\Omega}_{\theta_i}}\Big[\sup_{z_i\in\boldsymbol{\Omega}_{z_i}}|h_i(z_i,\theta_i)-h_i(z_i)|\Big]$$

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:

$$h_i(z_i)=\boldsymbol{\theta}_i^{*\mathrm{T}}\boldsymbol{\xi}_i(z_i)+\varepsilon_i^*(z_i) \quad (27)$$

其中:神经网络逼近误差$\varepsilon_i^*(z_i)$满足$|\varepsilon_i^*(z_i)|\leqslant\varepsilon_i$,$i=1,\cdots,n$。

考虑如下控制律:

$$v_i(t)=-\frac{1}{b_{i0}\beta_{i0}}[k_{i0}(t)|s_i|+|\hat{\boldsymbol{\theta}}_i^{\mathrm{T}}\boldsymbol{\xi}_i(z_i)|]\mathrm{sgn}(s_i) \quad (28)$$

$$k_{i0}=k_{i1}(t)+\frac{mk_{i2}}{2(1-\bar{\tau}_{\max})\max\{s_i^2,c_{s_i}^2\}}\cdot\sum_{j=1}^{i}\sum_{k=1}^{m}\int_{t-\tau_{\max}}^{t}\rho_{jk}^2(x_k(\tau))\mathrm{d}\tau \quad (29)$$

$$k_{i1}=\frac{k}{b_{i0}}\int_0^1\omega b_{i1}(\bar{\boldsymbol{x}}_i^+,\omega s+\beta_i)\mathrm{d}\omega \quad (30)$$

其中:k,k_{i2}为设计正常数。

自适应律:

$$\dot{\hat{\theta}}_i=\begin{cases}\eta_i(s_i\boldsymbol{\xi}_i(z_i)-\sigma_i\hat{\boldsymbol{\theta}}_i), & \text{当}\|\hat{\boldsymbol{\theta}}_i\|<M_{\theta_i},\\ & \text{或}\|\hat{\boldsymbol{\theta}}_i\|=M_{\theta_i},\text{且 }s_i\hat{\boldsymbol{\theta}}_i^{\mathrm{T}}\boldsymbol{\xi}_i(z_i)\leqslant 0;\\ \eta_i\Big(s_i\boldsymbol{\xi}_i(z_i)-\sigma_i\hat{\boldsymbol{\theta}}_i-s_i\dfrac{\hat{\boldsymbol{\theta}}_i\hat{\boldsymbol{\theta}}_i^{\mathrm{T}}}{\|\hat{\boldsymbol{\theta}}_i\|^2}\boldsymbol{\xi}_i(z_i)\Big), & \\ & \text{当}\|\hat{\boldsymbol{\theta}}_i\|=M_{\theta_i},\text{且 }s_i\hat{\boldsymbol{\theta}}_i^{\mathrm{T}}\boldsymbol{\xi}_i(z_i)>0。\end{cases} \quad (31)$$

$$\dot{\hat{\varepsilon}}_i=\eta_{i1}[s_i-\sigma_{i1}\hat{\varepsilon}_i]。 \quad (32)$$

其中:σ_i,σ_{i1},η_i,η_{i1}是正的设计常数。

3 稳定性分析

令$v=\frac{1}{2}\hat{\boldsymbol{\theta}}_i^{\mathrm{T}}\hat{\boldsymbol{\theta}}_i$,则类似于文献[12]中讨论可知,只要参数$\hat{\theta}_i(0)\in\boldsymbol{\Omega}_{\theta_i}$,则$\|\hat{\boldsymbol{\theta}}_i\|\leqslant M_{\theta_i}$,$\forall t\geqslant 0$,因此可提出如下定理。

定理 1 考虑对象(1),其控制律由式(28)~式(30)确定,自适应律由式(31)~式(32)确定,并满足假设式(1)~式(8),则对于初始条件,闭环系统是半全局一致终结有界。

1) $\hat{\boldsymbol{\theta}}_i\in\Big\{\hat{\boldsymbol{\theta}}_i\,\Big|\,\|\tilde{\boldsymbol{\theta}}_i\|^2\leqslant 2\eta_i\mu_i,\theta_i^*\in\boldsymbol{\Omega}_{\theta_i}\Big\}$, $\forall x_i(0)\in\boldsymbol{\Omega}_{i0}$ (33)

2) $x_i\in\boldsymbol{\Omega}_{ic}=\Big\{x_i\,\Big|\,\|x_i-x_d\|\leqslant c_{i0}(1+\|\Lambda_i\|\|\omega_i(0)\|+\Big[1+\frac{(1+\|\Lambda_i\|)c_{i0}}{\lambda_i}\Big]\max\{\sqrt{2\mu_i},c_{s_i}\}),\bar{\boldsymbol{x}}_{id}\in\boldsymbol{\Omega}_{id}\Big\}\subset\boldsymbol{\Omega}_i$ (34)

证明:1)考虑如下 Lyapunov 函数:

$$V_i(t)=V_{s_i}(t)+V_{u_i}(t)+\frac{1}{2\eta_i}\tilde{\boldsymbol{\theta}}_i^{\mathrm{T}}\tilde{\boldsymbol{\theta}}_i+\frac{1}{2\eta_{i1}}\tilde{\varepsilon}_i^2 \quad (35)$$

则:

$$\dot{V}_i(t) = \dot{V}_{s_i}(t) + \dot{V}_{u_i}(t) + \frac{1}{\eta_i}\tilde{\boldsymbol{\theta}}_i^{\mathrm{T}}\dot{\hat{\boldsymbol{\theta}}}_i + \frac{1}{\eta_{i1}}\tilde{\varepsilon}_i\dot{\hat{\varepsilon}}_i \leqslant s_i b_{i1}(\bar{\boldsymbol{x}}_i)\cdot\boldsymbol{K}_i^{\mathrm{T}}(t)\boldsymbol{\Phi}_i(t)v_i + s_i[\boldsymbol{\theta}_i^{*\mathrm{T}}\boldsymbol{\xi}_i(z_i) + \varepsilon_i^*] + \frac{p_i^{*2} + H_i^{*2}}{2} + \frac{m}{2(1-\bar{\tau}_{\max})}\left[1 - \frac{s_i^2}{c_{s_i}^2}\right]\sum_{j=1}^{i}\sum_{k=1}^{m}\rho_{jk}^2(x_k(\tau)) + \frac{1}{\eta_i}\tilde{\boldsymbol{\theta}}_i^{\mathrm{T}}\dot{\hat{\theta}}_i + \frac{1}{\eta_{i1}}\tilde{\varepsilon}_i\dot{\hat{\varepsilon}}_i \tag{36}$$

由假设(3)，可得：

$$b_{i1}(\bar{\boldsymbol{x}}_i)\boldsymbol{K}_i^{\mathrm{T}}(t)\boldsymbol{\Phi}_i(t) \geqslant b_{i0}\beta_{i0} \tag{37}$$

使用控制律(28)式～(30)式和自适应律(31)式～(32)式，及(37)式可得：

$$\dot{V}_i(t) \leqslant -s_i b_{i1}(\bar{\boldsymbol{x}}_i)\boldsymbol{K}_i^{\mathrm{T}}(t)\boldsymbol{\Phi}_i(t)\frac{1}{b_{i0}\beta_{i0}}[k_{i0}(t)\,|s_i| + |\boldsymbol{\theta}_i^{\mathrm{T}}\boldsymbol{\xi}_i(z_i)| + |\hat{\varepsilon}_i|]\mathrm{sgn}(s_i) + s_i[\boldsymbol{\theta}_i^{\mathrm{T}*}\boldsymbol{\xi}_i(z_i) + \varepsilon_i^*] + \frac{p_i^{*2} + H_i^{*2}}{2} + \frac{m}{2(1-\bar{\tau}_{\max})}\left[1 - \frac{s_i^2}{c_{s_i}^2}\right]\sum_{j=1}^{i}\sum_{k=1}^{m}\rho_{jk}^2(x_k(\tau)) + \frac{1}{\eta_i}\tilde{\boldsymbol{\theta}}_i^{\mathrm{T}}\dot{\hat{\theta}}_i + \frac{1}{\eta_{i1}}\tilde{\varepsilon}_i\dot{\hat{\varepsilon}}_i \leqslant -kV_{s_i} - k_{i2}V_{u_i} - \sigma_i\tilde{\boldsymbol{\theta}}_i^{\mathrm{T}}\hat{\theta}_i - \sigma_{i1}\tilde{\varepsilon}_i\hat{\varepsilon}_i + \frac{p_i^{*2} + H_i^{*2}}{2} + \frac{m(k_{i2}\tau_{\max}+1)}{2(1-\bar{\tau}_{\max})}\rho_{\max} \tag{38}$$

其中：$\rho_{\max} = \max\limits_{x_i \in \Omega_{c_{s_i}}}\sum\limits_{j=1}^{i}\sum\limits_{k=1}^{m}\rho_{jk}^2(x_k(\tau))$，由于下列不等式成立：

$$-\sigma_i\tilde{\boldsymbol{\theta}}_i^{\mathrm{T}}\hat{\theta}_i \leqslant -\frac{\sigma_i\|\tilde{\boldsymbol{\theta}}_i\|^2}{2} + \frac{\sigma_i\|\theta_i^*\|^2}{2} \tag{39}$$

$$-\sigma_{i1}\tilde{\varepsilon}_i\hat{\varepsilon}_i \leqslant -\frac{\sigma_{i1}\tilde{\varepsilon}_i^2}{2} + \frac{\sigma_{i1}\varepsilon_i^{*2}}{2} \tag{40}$$

将(39)式、(40)式代入(38)式可得：

$$\dot{V}_i(t) \leqslant -kv_{s_i} - k_{i2}V_{u_i} + \frac{m(k_{i2}\tau_{\max}+1)}{2(1-\bar{\tau}_{\max})}\rho_{\max} + \frac{\sigma_{i1}\varepsilon_i^{*2} + \sigma_i\|\theta_i^*\|^2 + H_i^{*2} + p_i^{*2}}{2} \tag{41}$$

令：

$$\lambda_{i0} = \min(k, k_{i2}, \sigma_i\eta_i, \sigma_{i1}\eta_{i1}) \tag{42}$$

$$\mu_{i0} = \frac{\sigma_{i1}\varepsilon_i^{*2} + \sigma_i\|\theta_i^*\|^2 + H_i^{*2} + p_i^{*2}}{2} \tag{43}$$

则：

$$\dot{V}_i(t) \leqslant -\lambda_{i0}V(t) + \mu_{i0} + \frac{m(k_{i2}\tau_{\max}+1)}{2(1-\bar{\tau}_{\max})}\rho_{\max} \tag{44}$$

在$[0,t]$上对(44)式求积分，可得：

$$V_i(t) \leqslant c_{i0} + [V_i(0) - c_{i0}]e^{-\lambda_{i0}t} \leqslant \mu_i \tag{45}$$

其中：

$$c_{i0} = \frac{\mu_{i0} + \dfrac{m(k_{i2}\tau_{\max}+1)}{2(1-\bar{\tau}_{\max})}\rho_{\max}}{\lambda_{i0}}, \mu_i = c_{i0} + V_i(0) \tag{46}$$

由(12)式，可知有 $s_i^2 \leqslant 2V_{s_i}(t) \leqslant 2V_i(t)$，类似地有 $\left\{\hat{\theta}_i \,\middle|\, \|\tilde{\boldsymbol{\theta}}_i\|^2 \leqslant 2\eta_i\mu_i, \theta_i^* \in \boldsymbol{\Omega}_{\theta_i}\right\}$。

2）定义 $\boldsymbol{\omega}_i = [e_{i1}, e_{i2}, \cdots, e_{i,n_i1}]^{\mathrm{T}} \in R^{n_i-1}$，根据(11)式，存在 $\dot{\omega}_i = \boldsymbol{A}_{s_i}\boldsymbol{\omega}_i + \boldsymbol{b}_{s_i}s_i$，其中 $s_i = [\boldsymbol{\Lambda}_i^{\mathrm{T}}, 1]e_i$，$\boldsymbol{\Lambda}_i = [\lambda_{i1}, \lambda_{i2}, \cdots, \lambda_{i,n_i-1}]^{\mathrm{T}}$，$\boldsymbol{b}_{s_i} = [0, \cdots, 0, 1]^{\mathrm{T}} \in R^{n_i-1}$，$\boldsymbol{A}_{s_i}$是一个稳定的矩阵，$c_{i0}$是一个正常数，满足$\|e^{A_{s_i}t}\| \leqslant c_{i0}e^{-\lambda_i t}$，$i = 1, \cdots, m$。

求解线性方程：$\dot{\omega}_i = \boldsymbol{A}_{s_i}\boldsymbol{\omega}_i + \boldsymbol{b}_{s_i}s_i$ 得：

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

因此，得 $\|\omega_i(t)\| \leqslant c_{i0}\|\omega_{i0}\|e^{-\lambda t} + c_{i0}\int_0^t e^{-\lambda(t-\tau)}|s_i(\tau)|\mathrm{d}\tau$，令 $\bar{\mu}_i = \max\{\sqrt{2\mu_i}, c_{s_i}\}$，所以：

$$\|\omega_i(t)\| \leqslant c_{i0}\|\omega_i(0)\| + \frac{c_{i0}\bar{\mu}_i}{\lambda_i} \tag{47}$$

注意到 $s_i = \boldsymbol{\Lambda}_i^{\mathrm{T}}\omega + e_{in_i}$，$\boldsymbol{e}_i = [\boldsymbol{\omega}_i^{\mathrm{T}}, e_{in_i}]^{\mathrm{T}}$，有 $\|\boldsymbol{e}_i\| \leqslant \|\boldsymbol{\omega}_i\| + |e_{in_i}| \leqslant (1 + \|\boldsymbol{\Lambda}_i\|)\|\boldsymbol{\omega}_i\| + |s_i|$，将此式代入(47)式，可得：

$$\|e_i\| \leqslant c_{i0}(1 + \|\boldsymbol{\Lambda}_i\|)\|\omega_i(0)\| + \left[1 + \frac{(1 + \|\boldsymbol{\Lambda}_i\|)c_{i0}}{\lambda_i}\right]\bar{\mu}_i \tag{48}$$

由于 $x = e + x_d$ 以及假设5)，因此有：

$$\|x_i\| \leqslant \|\boldsymbol{e}_i\| + \|x_{id}\| \leqslant c_{i0}(1 + \|\boldsymbol{\Lambda}_i\|)\|\omega_i(0)\| + \left[1 + \frac{(1 + \|\boldsymbol{\Lambda}_i\|)c_{i0}}{\lambda_i}\right]\max\{\sqrt{2\mu_i}, c_{s_i}\} + \|x_{id}\| \in L_\infty \tag{49}$$

由此可知，闭环系统是半全局一致有界的。

4　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：

$$\begin{cases}\dot{x}_{11}(t) = x_{12}(t) \\ \dot{x}_{12}(t) = x_{21}(t) - 0.3\sin(x_{21}(t)) + 0.1x_{11}^2(t - \tau_1(t)) + (2 - \sin^2(x_{11}(t)))u_1(t) + 0.5\sin(t) \\ \dot{x}_{21}(t) = x_{22}(t) \\ \dot{x}_{22}(t) = x_{11}^2u_1(t) + (x_{22}^2(t) + x_{11}(t) + 0.5\cdot\cos(x_{21}(t)))u_1^2(t) + 0.2x_{22}(t - \tau_2(t))\cdot\sin(x_{21}(t - \tau_2(t))) + (3 + \sin(x_{22}(t)))u_2(t) + 0.5\sin(t) \\ y_1(t) = x_{11}(t), y_2(t) = x_{21}(t)\end{cases} \tag{50}$$

其中：u_1，u_2 是死区输出。

控制目标：设计控制律 v_1 及 v_2，使得系统输出 y_1，y_2 跟踪轨迹 $y_{1d}(t) = 0.5[\sin(t) + \sin(0.5t)]$，$y_{2d}(t) = [\sin(0.5t) + 0.5\sin(1.5t)]$。仿真中选取隐节点数 $N = 25$，控制器设计参数 $\lambda_{11} = 1.5$，$\lambda_{21} = 2$，$k = 0.02$，$k_{12} = k_{22} = 0.05$，$\eta_1 = \eta_2 = \eta_{11} = \eta_{12} = 0.1$，$\sigma_1 = \sigma_2 = \sigma_{11} = \sigma_{21} = 0.01$，$\bar{\omega}_1 = \bar{\omega}_2 = 0.2$，选取 $g_{ir}(v_i) = k_{ir}\cdot(v_i - b_{ir})$，$g_{il}(v_i) = k_{il}(v_i - b_{il})$，死区参数 $k_{1l} = 0.5$，

$k_{1r}=1.5, k_{2l}=1.5, k_{2r}=2.5, b_{1l}=-0.5, b_{1r}=0.5, b_{2l}=-2.5, b_{2r}=2$，初值条件：$x_{11}(0)=x_{12}(0)=0, x_{21}(0)=x_{22}(0)=0$，时滞 $\tau_1(t)=\tau_2(t)=1+0.5\sin(t)$，$\tau_{\max}=2$，$\bar{\tau}_{\max}=0.6$，$M_{\theta_i}=4$，$\hat{\theta}_1(0)$ 与 $\hat{\theta}_2(0)$ 在区间$[-1,1]$上随机选取，$\hat{\varepsilon}_1=\hat{\varepsilon}_2=0.5$，仿真结果见图2～图7。仿真结果表明本文提出的控制方案具有良好的跟踪性能。

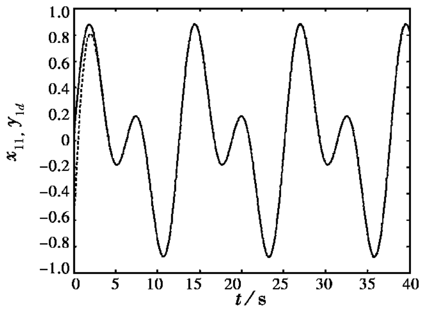

图2 状态 x_{11}(实线)和期望信号(虚线)的响应曲线

Fig. 2 x_{11}(solid line) and y_{1d}(dashed line)

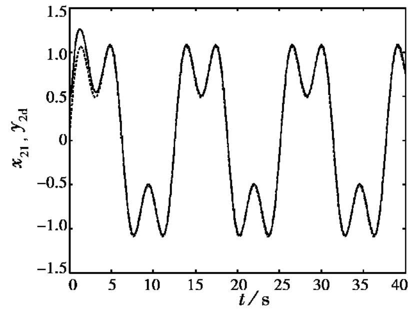

图3 状态 x_{21}(实线)和期望信号(虚线)响应的曲线

Fig. 3 x_{21}(solid line) and y_{2d}(dashed line)

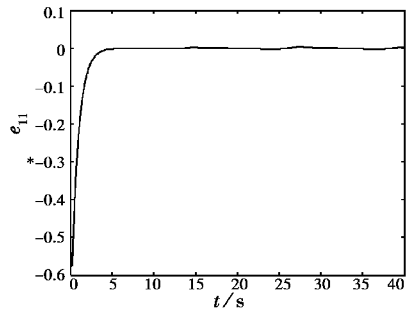

图4 跟踪误差曲线 e_{11}

Fig. 4 Tracking errors e_{11}

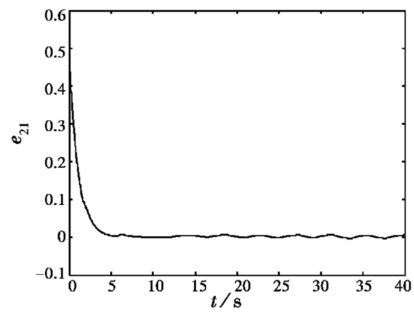

图5 跟踪误差曲线 e_{21}

Fig. 5 Tracking errors e_{21}

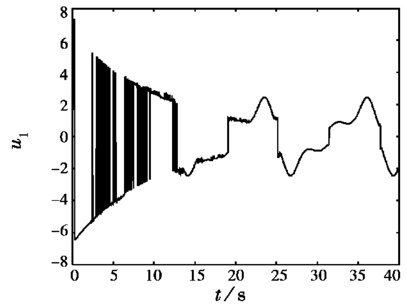

图6 控制律 u_1

Fig. 6 Control signal u_1 with time-varying delays

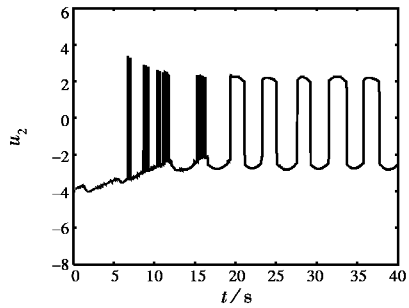

图7 控制律 u_2

Fig. 7 Control signal u_2 with time-varying delays

5 结论

针对一类具有未知死区和控制增益符号的已知的多输入多输出非线性时滞系统，基于滑模控制原理，提出一种稳定的自适应控制方案。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。并通过使用积分型李亚普诺夫函数，避免了控制器的奇异性问题。通过理论分析证明闭环系统是半全局一致终结有界。

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感器是否存在零漂。另外，因为本文的改进方法对这种偏差相当敏感，所以只要有足够多的数据量，使用这种方法可以检测到相当小的传感器零漂。

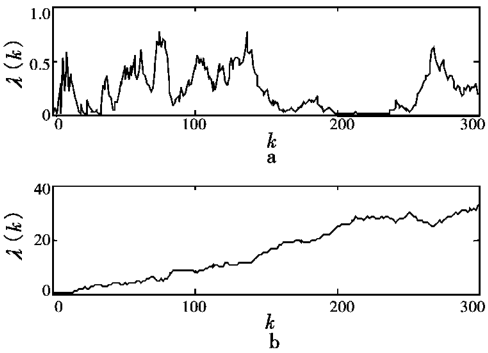

图 4　算例 3.2 的对数似然比曲线

Fig. 4　The logarithmic probability ratio curve in case 3.2

4　结论

从 Wald 序贯概率比方法用于故障诊断中残差检测时表现出的潜在缺陷性出发，提出了残差为正态分布条件下的一种改进方法，算例仿真结果表明这种方法在传感器缓变故障检测和零漂检测等方面具有较高实时性，同时这种方法从根本上消除了 Wald 序贯概率比方法用于残差判决时的延时问题。另外，理论上这种改进方法也同样适用于其他分布条件，只是相应计算无法做到正态分布这样简洁。

当然，虽然算例中该方法表现出了良好的性能，但由于该方法刚刚提出，还有待工程实践的检验和进一步完善。

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