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非线性时滞大系统自适应神经网络分散控制

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摘 要: 针对一类未知非线性时滞关联大系统,提出一种自适应神经网络分散跟踪控制方案. 采用神经网络逼近各子系统内部的非线性函数和关联项中的时滞非线性函数;利用占有方法处理时滞项,采用 Backstepping 技术设计分散控制律和参数自适应律. 基于 Lyapunov-Krasoviskii 泛函证明了闭环大系统所有信号半全局一致最终有界. 通过调节设计参数和增加神经元个数,可以实现任意输出跟踪精度. 实例仿真说明了该方案的可行性.

关键词: 时滞大系统; 神经网络; 分散控制; Backstepping
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Adaptive Neural Network Decentralized Control for Nonlinear Time-delay Large-scale Systems

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Abstract: A decentralized adaptive neural network (NN) tracking control approach is presented for a class of unknown large-scale nonlinear time-delay systems. Both the delay-independent functions of subsystems and the delay-dependent functions of interconnections are approximated by NNs. Domination method is used to deal with the time-delay terms. The decentralized control laws and the parameter adaptive laws are designed by Backstepping techique. Based on Lyapunov-Krasoviskii functional, the semi-global uniform ultimate boundedness (SGUUB) of all signals in the closed-loop system is proved. The arbitrary output tracking accuracy is achieved by tuning the design parameters and increasing the neural node number. An illustrative simulation example shows the feasibility.

Key words: Delayed large-scale systems; Neural network; Decentralized control; Backstepping

1 引 言

关联大系统是由许多相互关联、相互作用的子系统共同构成的大规模系统,它在诸多领域普遍存在. 分散控制是指利用组成大系统的各局部子系统信息构成若干局部控制器,以实现整个大系统的控制. 与集中控制相比,分散控制结构简单、经济实用,最近在这一领域已经取得了一些重要的研究成果[1~8]. 分散控制所研究的关键问题之一是对关联项的处理,文献[1,2]要求非线性关联项被一阶或高阶多项式所界定,并满足匹配条件;文献[3,4]要求关联项被已知函数所界定(或关联项为已知函数),但不满足匹配条件;文献[5]要求关联项被已知函数乘以未知参数所界定;文献[6]采用模糊神经网络逼近未知的非线性关联项,但仍然要求系统满足匹配条件. 另一方面,对非线性时滞大系统的分散控制的研究也取得了一些重要成果[7,8]. 文献[7]为一类带有非线性关联项的时滞大系统提出了一种分散控制方案,采用自适应技术估计关联项的上界;文献[8]针对一类非线性随机输出反馈大系统,提出了一种分散镇定方案,但仍然要求关联项被已知函数界定.

本文针对一类通过时滞输出关联的未知非线性大系统,提出了一种自适应神经网络分散跟踪控制

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方案. 因为采用神经网络逼近非线性时滞关联项, 所以假定系统中的光滑时滞函数是完全未知的, 这就大大放松了对非线性时滞函数的要求. 在稳定化函数和控制律中, 采用参考信号 $y_r(t-\tau)$ 取代输出信号 $y(t-\tau)$, 从而避免了在Backstepping 设计过程中对 $y(t-\tau)$ 求导. 最后通过一个仿真实例, 验证了算法的可行性和控制器的泛化能力.

2 问题描述

考虑由 N 个子系统组成的未知非线性输出时滞关联大系统. 其中第 i 个子系统的动态方程为

$$\begin{cases} \dot{x}_{i,j} = x_{i,j+1} + f_{i,j}(\bar{x}_{i,j}) + h_{i,j}(Y(t-\tau)), \\ \qquad j = 1,\cdots,n_i - 1; \\ \dot{x}_{i,n_i} = u_i + f_{i,n_i}(\bar{x}_{i,n_i}) + h_{i,n_i}(Y(t-\tau)); \\ y_i = x_{i,1}. \end{cases} \tag{1}$$

其中: $x_i = [x_{i,1},\cdots,x_{i,n_i}]^{\mathrm T} \in R^{n_i}$, $u_i \in R$ 和 $y_i \in R$ 分别表示第 i 个子系统的状态、控制输入和输出; $\bar{x}_{i,j} := [x_{i,1},\cdots,x_{i,j}]^{\mathrm T} \in R^j$, $Y(t-\tau) = [y_1(t-\tau_1),\cdots,y_N(t-\tau_N)]^{\mathrm T} \in R^N$; $f_{i,j}(\cdot): R^j \to R$ 表示子系统内部的未知连续函数; $h_{i,j}(\cdot): R^N \to R$ 表示各子系统之间相互作用的未知连续时滞关联项; $\tau_1,\cdots,\tau_N$ 表示各子系统的已知时间延迟, 若参考信号为常数, 则不要求时间延迟已知.

注 1 为了清楚地表达本文的主要思想, 避免重复工作, 假定系统(1) 的实控系数(控制输入 u_1 的系数) 为 1. 通过构建Nussbaum 增益函数的方法, 本文的结果完全可以推广到实控系数未知的情况.

本文的目标是为关联大系统(1) 设计自适应神经网络分散控制器 $u_i(t)$, 使子系统输出 $y_i(t)$ 跟踪给定的参考信号 $y_{r,i}(t)$, 同时保持闭环系统所有信号半全局一致有界. 在紧集 $\Omega_{i,j} \subset R^j$ 和 $\Omega \subset R^N$ 上, 连续函数 $f_{i,j}(\bar{x}_{i,j})$ 和 $h_{i,j}(Y(t-\tau))$ 分别通过如下线性参数化网络逼近[9]:

$$\begin{cases} f_{i,j}(\bar{x}_{i,j}) = \xi_{i,j}(\bar{x}_{i,j})^{\mathrm T}\varsigma_{i,j} + \epsilon^f_{i,j}(\bar{x}_{i,j}), \\ h_{i,j}(Y_\tau) = \zeta_{i,j}(Y_\tau)^{\mathrm T}\theta_{i,j} + \epsilon^h_{i,j}(Y_\tau). \end{cases} \tag{2}$$

其中: $Y_\tau := Y(t-\tau)$, 为研究方便, 下文也采用这一符号; $\xi_{i,j}(\cdot): \Omega_{i,j} \to R^{p_{i,j}}$ 和 $\zeta_{i,j}(\cdot): \Omega \to R^{q_{i,j}}$ 为已知的光滑基函数; $p_{i,j}$ 和 $q_{i,j}$ 为相应的神经元个数; $\epsilon^f_{i,j}$ 和 $\epsilon^h_{i,j}$ 为内在逼近误差; $\varsigma_{i,j} \in R^{p_{i,j}}$, $\theta_{i,j} \in R^{q_{i,j}}$ 为最优权值, 定义如下:

$$\begin{cases} \varsigma_{i,j} := \arg \min\limits_{\hat{\varsigma}_{i,j} \in R^{p_{i,j}}} \Big\{ \sup\limits_{\bar{x}_{i,j} \in \Omega_{i,j}} \big| f_{i,j}(\bar{x}_{i,j}) - \\ \qquad \xi_{i,j}(\bar{x}_{i,j})^{\mathrm T}\hat{\varsigma}_{i,j} \big| \Big\}, \\ \theta_{i,j} := \arg \min\limits_{\hat{\theta}_{i,j} \in R^{q_{i,j}}} \Big\{ \sup\limits_{Y_\tau \in \Omega} \big| h_{i,j}(Y_\tau) - \\ \qquad \zeta_{i,j}(Y_\tau)^{\mathrm T}\hat{\theta}_{i,j} \big| \Big\}. \end{cases} \tag{3}$$

定义网络重构误差为

$$\upsilon_{i,j}(\bar{x}_{i,j}, Y_\tau) = \epsilon^f_{i,j}(\bar{x}_{i,j}) + \epsilon^h_{i,j}(Y_\tau), \quad j = 1,\cdots,n_i. \tag{4}$$

将式(2) 代入(1), 得

$$\begin{cases} \dot{x}_{i,j} = \\ x_{i,j+1} + \phi_{i,j}(\bar{x}_{i,j})^{\mathrm T}\varsigma_i + \varphi_{i,j}(Y_\tau)^{\mathrm T}\theta_i + \upsilon_{i,j}, \\ \qquad j = 1,\cdots,n_i - 1; \\ \dot{x}_{i,n_i} = \\ u_i + \phi_{i,n_i}(\bar{x}_{i,n_i})^{\mathrm T}\varsigma_i + \varphi_{i,n_i}(Y_\tau)^{\mathrm T}\theta_i + \upsilon_{i,n_i}; \\ y_i = x_{i,1}. \end{cases} \tag{5}$$

其中

$$\varsigma_i = [\varsigma^{\mathrm T}_{i,1},\cdots,\varsigma^{\mathrm T}_{i,n_i}]^{\mathrm T},$$

$$\theta_i = [\theta^{\mathrm T}_{i,1},\cdots,\theta^{\mathrm T}_{i,n_i}]^{\mathrm T},$$

$$\phi_{i,j} = \Big[0^{\mathrm T}_{1\times(\sum_{k=1}^{j-1}p_{i,k})} \Big| \xi^{\mathrm T}_{i,j(1\times p_{i,j})} \Big| 0^{\mathrm T}_{1\times(\sum_{k=j+1}^{n_i}p_{j,k})}\Big]^{\mathrm T},$$

$$\varphi_{i,j} = \Big[0^{\mathrm T}_{1\times(\sum_{k=1}^{j-1}q_{i,k})} \Big| \zeta^{\mathrm T}_{i,j(1\times q_{i,j})} \Big| 0^{\mathrm T}_{1\times(\sum_{k=j+1}^{n_i}q_{i,k})}\Big]^{\mathrm T}.$$

本文作以下假设:

假设 1[9] 在紧集 $\Omega_{i,j}$ 和 Ω 上, 第 i 个子系统的网络重构误差 $\upsilon_{i,j}$ 满足 $|\upsilon_{i,j}(\bar{x}_{i,j}, Y_\tau)| \le \psi_i$, 其中 $\psi_i \ge 0$ 为未知常数.

假设 2[10] 对 $i = 1,\cdots,N$, 参考信号 $y_{r,i}(t)$ 及其前 n_i 阶导数已知, 且在 $[-\tau_i, +\infty)$ 上一致有界.

注 2 假设 2 是Backstepping 设计中所作的一般性假设. 若采用文献[11] 的思想, 这一假设可以放松, 只要求参考信号一阶可导, 而且可以简化Backstepping 设计过程. 但为了突出本文的设计思想, 避免重复别人的工作, 本文仍保持这一假设.

假设 3 所选择的基函数 $\zeta_{i,j}(\cdot)$ 满足Lipschitz 条件, 因此

$$|(\varphi_{i,j}(Y_\tau) - \varphi_{i,j}(Y_{r\tau})^{\mathrm T}\theta_i| \le \sum_{m=1}^{N} |y_m(t-\tau_m) - y_{r,m}(t-\tau_m)| l_{i,j,m}. \tag{6}$$

其中: $Y_{r\tau} := [y_{r,1}(t-\tau_1),\cdots,y_{r,N}(t-\tau_N)]^{\mathrm T}$, $l_{i,j,m} \ge 0$ 为未知常数.

注 3 假设3 具有一般性, 很多基函数(比如常用的高斯函数) 都满足这一假设.

3 自适应 NN 控制设计

下面采用Backstepping 技术设计自适应NN 控制器, 限于篇幅, 详细推导过程省略. 进行如下坐标变换:

$$\begin{cases} z_{i,1} = y_i - y_{r,1}, \\ z_{i,j} = x_{i,j} - \alpha_{i,j-1} - y^{(j-1)}_{r,i}, \\ \qquad j = 2,\cdots,n_i. \end{cases} \tag{7}$$

设计稳定化函数为

$$\begin{cases}\alpha_{i,1} = \\ -a_{i,1}z_{i,1} - \omega^{\mathrm{T}}_{\vartheta_i,1}\hat{\vartheta}_i - \omega^{\mathrm{T}}_{\theta_i,1}\hat{\theta}_i - \omega_{\psi_i}\hat{\psi}_i, \\ \alpha_{i,j} = \\ -z_{i,j-1} - a_{i,j}z_{i,j} - \sum\limits_{k=2}^{j-1}\sigma_{i,j,k}z_{i,k} - \\ \omega^{\mathrm{T}}_{\vartheta_i,j}\hat{\vartheta}_i - \omega^{\mathrm{T}}_{\theta_i,j}\hat{\theta}_i - \omega_{\psi_i,j}\hat{\psi}_i - \Delta_{i,j}, \\ \qquad j = 1,\cdots,n_i.\end{cases} \tag{8}$$

为研究方便, 引入符号 $\alpha_{i,0} = 0$.

$$a_{i,1} =$$
$$c_{i,1} + \sum_{m=1}^{N}\sum_{j=1}^{n_m}\Big[1 + \frac{1}{2}j(j-1)\Big] + \omega_{\Theta_i,1}\hat{\Theta}_i,$$
$$a_{i,j} = c_{i,j} + \omega_{\Theta_i,j}\hat{\Theta}_i,$$
$$\omega_{\Theta_i,j} = \frac{1}{2} + \frac{1}{2}\sum_{k=1}^{j-1}\Big(\frac{\partial\alpha_{i,j-1}}{\partial x_{i,k}}\Big),$$
$$\sigma_{i,j,k} =$$
$$-\frac{\partial\alpha_{i,j-1}}{\partial\hat{\vartheta}_i}\Gamma_{\vartheta_i}\omega_{\vartheta_i,k} - \frac{\partial\alpha_{i,j-1}}{\partial\hat{\theta}_i}\Gamma_{\theta_i}\omega_{\theta_i,k} -$$
$$\frac{\partial\alpha_{i,j-1}}{\partial\hat{\psi}_i}\gamma_{\psi_i}\omega_{\psi_i,k} - \frac{\partial\alpha_{i,j-1}}{\partial\hat{\Theta}_i}\gamma_{\Theta_i}\omega_{\Theta_i,k}z_{i,k},$$
$$\omega_{\vartheta_i,j} = \phi_{i,j}(\bar{x}_{i,j}) - \sum_{k=1}^{j-1}\frac{\partial\alpha_{i,j-1}}{\partial x_{i,k}}\phi_{i,k}(\bar{x}_{i,k}),$$
$$\omega_{\theta_i,j} = \varphi_{i,j}(Y_{r\tau}) - \sum_{k=1}^{j-1}\frac{\partial\alpha_{i,j-1}}{\partial x_{i,k}}\varphi_{i,k}(Y_{r\tau}),$$
$$\omega_{\psi_i,j} = \beta_{i,j}\tanh\Big(\frac{\beta_{i,j}z_{i,j}}{\epsilon}\Big),$$
$$\beta_{i,j} = 1 + \frac{1}{2}\sum_{k=1}^{j-1}\Big[1 + \Big(\frac{\partial\alpha_{i,j-1}}{\partial x_{i,k}}\Big)^2\Big],$$
$$\Delta_{i,j} =$$
$$-\sum_{k=1}^{j-1}\frac{\partial\alpha_{i,j-1}}{\partial x_{i,k}}x_{i,k+1} - \sum_{k=1}^{j-1}\frac{\partial\alpha_{i-1,j}}{\partial Y_{r\tau}^{(k-1)}}Y_{r\tau}^{(k)} -$$
$$\sum_{k=1}^{j-1}\frac{\partial\alpha_{i,j-1}}{\partial y_{r,i}^{(k-1)}}y_{r,i}^{(k)} - \frac{\partial\alpha_{i,j-1}}{\partial\hat{\vartheta}_i}\Gamma_{\vartheta_i}(\tau_{\vartheta_i,j} - \iota\hat{\vartheta}_i) -$$
$$\frac{\partial\alpha_{i,j-1}}{\partial\hat{\theta}_i}\Gamma_{\theta_i}(\tau_{\theta_i,j} - \iota\hat{\theta}_i) - \frac{\partial\alpha_{i,j-1}}{\partial\hat{\psi}_i}\gamma_{\psi_i}(\tau_{\psi_i,j} -$$
$$\iota\hat{\psi}_i) - \frac{\partial\alpha_{i,j-1}}{\partial\hat{\Theta}_i}\gamma_{\Theta_i}(\tau_{\Theta_i,j} - \iota\hat{\Theta}_i).$$

其中: $\hat{\Theta}_i$ 表示 $\Theta_i = \max\limits_{1\le j\le n_i}\Big\{\sum\limits_{m=1}^{N}l^2_{i,j,m}\Big\}$ 的估计; $\Gamma_{\vartheta_i}, \Gamma_{\theta_i}, \gamma_{\Theta_i}, \gamma_{\psi_i} > 0$ 表示自适应增益; $\epsilon, \iota > 0$ 为设计参数.

选择调节函数为

$$\begin{cases}\tau_{\vartheta_i,1} = \omega_{\vartheta_i,1}z_{i,1},\ \tau_{\vartheta_i,j} = \tau_{\vartheta_i,j-1} + \omega_{\vartheta_i,j}z_{i,j}, \\ \tau_{\theta_i,1} = \omega_{\theta_i,1}z_{i,1},\ \tau_{\theta_i,j} = \tau_{\theta_i,j-1} + \omega_{\theta_i,j}z_{i,j}, \\ \tau_{\psi_i,1} = \omega_{\psi_i,1}z_{i,1},\ \tau_{\psi_i,j} = \tau_{\psi_i,j-1} + \omega_{\psi_i,j}z_{i,j}, \\ \tau_{\Theta_i,1} = \omega_{\Theta_i,1}z^2_{i,1},\ \tau_{\Theta_i,j} = \tau_{\Theta_i,j-1} + \omega_{\Theta_i,j}z^2_{i,j}, \\ \qquad j = 1,2,\cdots,n_i,\end{cases} \tag{9}$$

最后的调节函数用作自适应律

$$\begin{cases}\dot{\hat{\vartheta}}_i = \Gamma_{\vartheta_i}(\tau_{\vartheta_i,n_i} - \iota\hat{\vartheta}_i) = \Gamma_{\vartheta_i}(W_{\vartheta_i}z_i - \iota\hat{\vartheta}_i), \\ \dot{\hat{\theta}}_i = \Gamma_{\theta_i}(\tau_{\theta_i,n_i} - \iota\hat{\theta}_i) = \Gamma_{\theta_i}(W_{\theta_i}z_i - \iota\hat{\theta}_i), \\ \dot{\hat{\psi}}_i = \gamma_{\psi_i}(\tau_{\psi_i,n_i} - \iota\hat{\psi}_i) = \gamma_{\psi_i}(W_{\psi_i}z_i - \iota\hat{\psi}_i), \\ \dot{\hat{\Theta}}_i = \gamma_{\Theta_i}(\tau_{\Theta_i,n_i} - \iota\hat{\Theta}_i) = \gamma_{\Theta_i}\sum\limits_{j=1}^{n_i}(\omega_{\Theta_i,j}z^2_{i,j} - \iota\hat{\Theta}_i).\end{cases} \tag{10}$$

其中

$$z_i = [z_{i,1},\cdots,z_{i,n_i}]^{\mathrm{T}}, W_{\vartheta_i} = [\omega_{\vartheta_i,1},\cdots,\omega_{\vartheta_i,n_i}],$$
$$W_{\theta_i} = [\omega_{\theta_i,1},\cdots,\omega_{\theta_i,n_i}], W_{\psi_i} = [\omega_{\psi_i,1},\cdots,\omega_{\psi_i,n_i}].$$

最后的稳定化函数用作控制律

$$u_i = \alpha_{n_i} + y_{r,i}^{(n_i)} =$$
$$-z_{i,n_i-1} - a_{i,n_i}z_{i,n_i} - \sum_{k=2}^{n_i-1}\sigma_{i,n_i,k}z_{i,k} -$$
$$\omega^{\mathrm{T}}_{\vartheta_i,n_i}\hat{\vartheta}_i - \omega^{\mathrm{T}}_{\theta_i,n_i}\hat{\theta}_i - \omega_{\psi_i,n_i}\hat{\psi}_i - \Delta_{i,n_i} + y_{r,i}^{(n_i)}. \tag{11}$$

将式(8) 代入(7), 得误差动态方程

$$\begin{cases}\dot{z}_{i,1} = z_{i,2} - a_{i,1}z_{i,1} + \omega^{\mathrm{T}}_{\vartheta_i,1}\tilde{\vartheta}_i + \\ \qquad \omega^{\mathrm{T}}_{\theta_i,1}\tilde{\theta}_i - \omega_{\psi_i}\hat{\psi}_i + \zeta_{i,1} + \Lambda_{i,1}, \\ \dot{z}_{i,j} = -z_{i,j-1} - a_{i,j}z_{i,j} + z_{i,j+1} - \\ \quad \sum\limits_{k=2}^{j-1}\sigma_{i,j,k}z_{k,j} + \sum\limits_{k=j+1}^{n_i}\sigma_{i,k,j}z_{i,k} + \\ \quad \omega^{\mathrm{T}}_{\vartheta_i,j}\tilde{\vartheta}_i + \omega^{\mathrm{T}}_{\theta_i,j}\tilde{\theta}_i - \omega_{\psi_i}\hat{\psi}_{i,j} + \zeta_{i,j} + \Lambda_{i,j}, \\ \qquad j = 2,\cdots,n_i.\end{cases} \tag{12}$$

其中

$$\zeta_{i,j} = \upsilon_{i,j} - \sum_{k=1}^{j-1}\frac{\partial\alpha_{i,j-1}}{\partial x_{i,k}}\upsilon_{i,k}, \tag{13}$$

$$\Lambda_{i,j} =$$
$$[\varphi_{i,j}(Y_\tau) - \varphi_{i,j}(Y_{r\tau})]\theta_i -$$
$$\sum_{k=1}^{j-1}\frac{\partial\alpha_{i,j-1}}{\partial x_{i,k}}[\varphi_{i,k}(Y_\tau) - \varphi_{i,k}(Y_{r\tau})]^{\mathrm{T}}\theta_i. \tag{14}$$

利用不等式[9]

$$|\eta| \le \eta\tanh(\eta/\epsilon) + \kappa\epsilon, \kappa = 0.278\,5, \epsilon > 0,$$

根据 $\beta_{i,j}, \psi_i, \omega_{\psi_i,j}$ 的定义, 式(13) 满足

$$z_{i,j}\zeta_{i,j} \le \psi_i z_{i,j}\omega_{\psi_i,j} + \Psi_i\kappa\epsilon. \tag{15}$$

通过不等式(6) 和 Youg 不等式, 时滞项(14) 满足以下不等式:

$$\sum_{i=1}^{N}\sum_{j=1}^{n_i}z_{i,j}\Lambda_{i,j} \le$$
$$\sum_{i=1}^{N}\Big[\frac{1}{2}\Theta_i\sum_{j=1}^{n_i}\Big(1 + \sum_{k=1}^{j-1}\Big(\frac{\partial\alpha_{i,j-1}}{\partial x_{i,k}}\Big)^2z^2_{i,j}\Big) +$$
$$\frac{1}{2}z^2_{i,1}(t-\tau_j)\sum_{m=1}^{N}\sum_{j=1}^{n_m}\Big(1 + \frac{1}{2}j(j-1)\Big)\Big]. \tag{16}$$

定理 1 在假设 1～假设 3 下, 由系统(1), 自适应律(10) 和控制律(11) 组成的闭环大系统具有以下特点:

1) 跟踪误差满足

$$\lim_{t\to\infty}\frac{1}{t}\int|z_{i,1}(\sigma)|^2 d\sigma \leq \frac{\lambda}{c_0},\ i=1,\cdots,N,\tag{17}$$

其中 λ 和 c_0 将在证明中给出.

2) 所有信号 $\hat{\wp}_i, \hat{\Psi}_i, \hat{\Psi}_i, \hat{\Theta}_i, x_i, u_i, i=1,\cdots,N$, 半全局一致有界.

证明 定义 Lyapunov-Krasoviskii 泛函如下:

$$V=\sum_{i=1}^{N}\Big[\frac{1}{2}z_i^{\mathrm T}z_i+\frac{1}{2}\tilde{\wp}_i^{\mathrm T}\Gamma_{\wp_i}^{-1}\tilde{\wp}_i+\frac{1}{2}\tilde{\theta}_i^{\mathrm T}\Gamma_{\theta_i}^{-1}\tilde{\theta}_i+\frac{1}{2}\gamma_{\Psi_i}^{-1}\tilde{\Psi}_i^2+\frac{1}{2}\gamma_{\Theta_i}^{-1}\tilde{\Theta}_i^2+\sum_{m=1}^{N}\sum_{j=1}^{n_m}\Big(1+\frac{1}{2}j(j-1)\Big)\int_{-\tau_i}z_{i,1}^2(\sigma)d\sigma\Big].\tag{18}$$

沿式(10) 和(12), 对 V 求导, 得

$$\begin{aligned}\dot V=&\sum_{i=1}^{N}\Big[-\sum_{j=1}^{n_i}a_{i,j}z_{i,j}^2-\tilde{\Theta}_i\sum_{j=1}^{n_i}z_{i,j}^2\omega_{\Theta_i,j}-\\&\Psi_i\sum_{j=1}^{n_i}z_{i,j}\omega_{\Psi_i,j}+\sum_{j=1}^{n_i}z_{i,j}\zeta_{i,j}+\\&\sum_{j=1}^{n_i}z_{i,j}\Lambda_{i,j}+\iota(\tilde{\wp}_i^{\mathrm T}\hat{\wp}_i+\tilde{\theta}_i^{\mathrm T}\hat{\theta}_i+\tilde{\Psi}_i\hat{\Psi}_i+\\&\tilde{\Theta}_i\hat{\Theta}_i)+\frac{1}{2}z_{i,1}^2\sum_{m=1}^{N}\sum_{j=1}^{n_m}\Big(1+\frac{1}{2}j(j-1)\Big)-\\&\frac{1}{2}z_{i,1}^2(t-\tau_i)\sum_{m=1}^{N}\sum_{j=1}^{n_m}\Big(1+\frac{1}{2}j(j-1)\Big)\Big].\end{aligned}\tag{19}$$

将 $a_{i,j}$ 代入式(19), 注意到 $\hat{\Theta}_i+\tilde{\Theta}_i=\Theta_i$ 和 $\omega_{\Theta_i,j}$ 的定义, 并利用不等式(15), (16) 和不等式[9]

$$\begin{aligned}&\tilde{\wp}_i^{\mathrm T}\hat{\wp}_i+\tilde{\theta}_i^{\mathrm T}\hat{\theta}_i+\tilde{\Psi}_i\hat{\Psi}_i+\tilde{\Theta}_i\hat{\Theta}_i\leq\\&-\frac{1}{2}(\|\tilde{\wp}_i\|^2+\|\tilde{\theta}_i\|^2+\tilde{\Psi}_i^2+\tilde{\Theta}_i^2)+\\&\frac{1}{2}(\|\wp_i\|^2+\|\theta_i\|^2+\Psi_i^2+\Theta_i^2),\end{aligned}\tag{20}$$

其中 $\|\cdot\|$ 表示 2-范数. 经过直接计算, 得

$$\begin{aligned}\dot V\leq&\sum_{i=1}^{N}\Big[-\sum_{j=1}^{n_i}c_{i,j}z_{i,j}^2-\frac{1}{2}\iota(\|\tilde{\wp}_i\|^2+\\&\|\tilde{\theta}_i\|^2+\tilde{\Psi}_i^2+\tilde{\Theta}_i^2)\Big]+\lambda.\end{aligned}\tag{21}$$

其中

$$\lambda=\sum_{i=1}^{N}\Big[n_i\kappa\Psi_i\epsilon+\frac{1}{2}\iota(\|\theta_i\|^2+\|\wp_i\|^2+\Theta_i^2+\Psi_i^2)\Big].$$

记 $c_0=\min_{1\leq i\leq N,1\leq j\leq n_i}\{c_{i,j}\}$, 由式(21), 得

$$\begin{aligned}c_0\int z_{i,1}^2(\sigma)d\sigma\leq&\int\sum_{i=1}^{N}\sum_{j=1}^{n_i}c_{i,j}z_{i,j}^2(\sigma)d\sigma\leq\\&-\int\dot V(\sigma)d\sigma+\int\lambda d\sigma\leq V(0)+\lambda t.\end{aligned}\tag{22}$$

由式(22), 可证式(17) 成立. 令 $\pi=[z_1^{\mathrm T},\cdots,z_N^{\mathrm T},\tilde{\wp}_1^{\mathrm T},\cdots,\tilde{\wp}_N^{\mathrm T},\tilde{\theta}_1^{\mathrm T},\cdots,\tilde{\theta}_N^{\mathrm T},\tilde{\Psi}_1,\cdots,\tilde{\Psi}_N,\tilde{\Theta}_1,\cdots,\tilde{Q}_N]^{\mathrm T}$, 由式(21), 有

$$\dot V(\pi)\leq-\bar c\|\pi\|^2+\lambda,\tag{23}$$

其中 $\bar c=\min\{c_0,\frac{1}{2}\iota\}$. 根据泛函微分方程 Lyapunov 稳定性理论[10], 式(23) 说明信号 π 是半全局一致有界的. 从而 $\hat{\wp}_i,\hat{\theta}_i,\hat{\Psi}_i,\hat{\Theta}_i$ 半全局一致有界, 由坐标变换(7) 和假设 2, 可依次得到 $x_{i,1},x_{i,2},\cdots,x_{i,n_i},u_i(i=1,\cdots,N)$ 半全局一致有界.

4 仿真研究

考虑以下二阶输出时滞关联大系统:

$$\Sigma_1:\begin{cases}\dot x_{1,1}=x_{1,2}+f_{1,1}(x_{1,1})+h_{1,1}(Y_\tau),\\ \dot x_{1,2}=u_1+f_{1,2}(\bar x_{1,2})+h_{1,2}(Y_\tau);\end{cases}$$

$$\Sigma_2:\begin{cases}\dot x_{2,1}=x_{2,2}+f_{2,1}(x_{2,1})+h_{2,1}(Y_\tau),\\ \dot x_{2,2}=u_2+f_{2,2}(\bar x_{2,2})+h_{2,2}(Y_\tau);\end{cases}$$

其中: $y_1=x_{1,1}$ 和 $y_2=x_{2,1}$ 为系统输出. 未知函数为

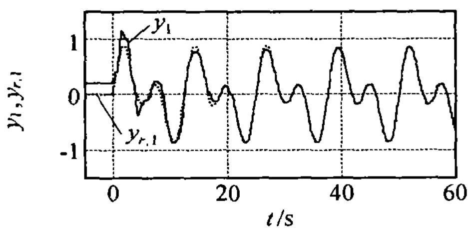
$$\begin{aligned}&f_{1,1}=\sin(x_{1,1}),f_{1,2}=x_{1,1}+x_{1,2},\\&f_{2,1}=0.1x_{2,1}^3,f_{2,2}=x_{2,1}x_{2,2}\\&h_{1,1}=y_2(t-\tau_2)\cos y_1(t-\tau_1),\\&h_{1,2}=y_2(t-\tau_2)+y_1(t-\tau_1),\\&h_{2,1}=\sin(y_2(t-\tau_2)y_1(t-\tau_1)),\\&h_{2,2}=\tanh(y_2(t-\tau_2)y_1(t-\tau_1)).\end{aligned}$$

参考信号设定为

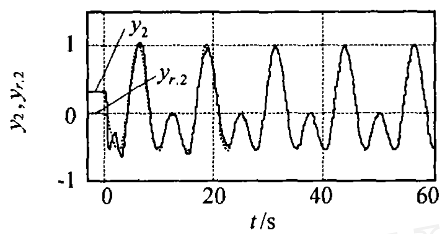
$$\begin{aligned}&y_{r,1}(t)=0.5\sin(t)+0.5\sin(0.5t),\\&y_{r,2}(t)=0.5\cos(t)-0.5\cos(0.5t),\end{aligned}$$

时滞 $\tau_1=5,\tau_2=3$. 根据本文提出的设计方案(限于篇幅, 这里只给出设计参数), 函数逼近器均采用高斯 RBF[9], 用于逼近 $f_{1,1}$ 和 $f_{2,1}$ 的神经网络节点共 9 个, 基函数中心均匀覆盖区间[-1, 1], 基函数宽度定为 0.5. 其余的函数逼近器神经网络节点共 9×9 = 81 个, 基函数中心均匀覆盖区间[-1, 1]×[-1, 1], 基函数宽度仍定为 0.5. 在实际仿真中, 选择控制参数为 $c_{i,j}=0.1(i,j=1,2)$, $\zeta=0.001$, $\epsilon=0.01$, 自适应增益为 $\Gamma_{\theta_i}=\Gamma_{\wp_i}=2I$, $\gamma_{\Theta_i}=\gamma_{\Psi_i}=0.2$, $i=1,2$, 初始条件取为 $x_{11}(t)=0.2,t\in[-\tau_1,0]$, $x_{21}(t)=0.3,t\in[-\tau_2,0]$, 其余均取为 0. 仿真结果如图 1 所示.

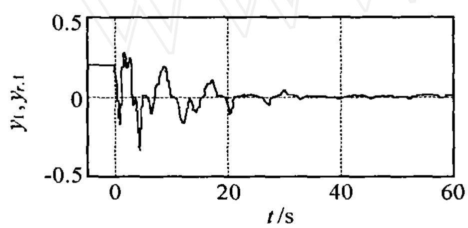
为了说明控制器的泛化能力及其应用, 本文在保持控制器设计参数不变的情况下, 将其用于控制



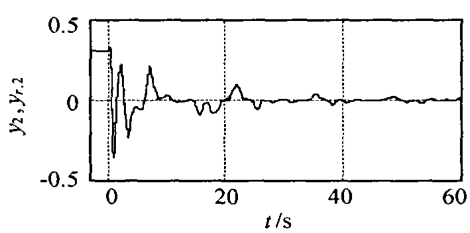
(a)　输出 y_1 和参数信号 $y_{r,1}$



(b)　输出 y_2 和参数信号 $y_{r,2}$



(c)　跟踪误差 $y_1 - y_{r,1}$



(d)　跟踪误差 $y_2 - y_{r,2}$

图 1　大系统 Σ_1-Σ_2 的仿真结果

通过弹力滞后的弹簧相互关联的倒立摆大系统. 该系统在文献[6]中已有研究, 但未考虑弹力滞后.

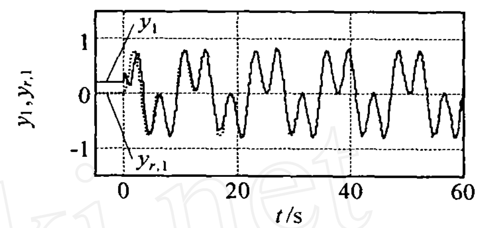
Σ_3:

$$\begin{cases} \dot{x}_{1,1} = x_{1,2}, \\ \dot{x}_{1,2} = \\ \dfrac{1}{J_1}u_1 + \left(\dfrac{m_1 g r}{J_1} - \dfrac{kr^2}{4J_1}\right)\sin(x_{1,1}(t-\tau_1)) + \\ \dfrac{kr}{2J_1}(l-b) + \dfrac{kr^2}{4J_1}\sin(x_{2,1}(t-\tau_2)); \end{cases}$$

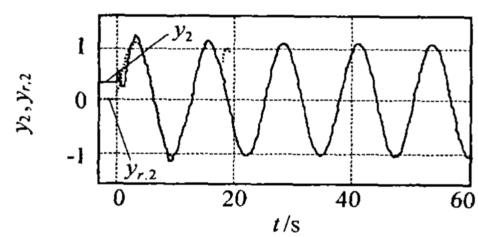
Σ_4:

$$\begin{cases} \dot{x}_{2,1} = x_{2,2}, \\ \dot{x}_{2,2} = \\ \dfrac{1}{J_1}u_2 + \left(\dfrac{m_2 g r}{J_2} - \dfrac{kr^2}{4J_2}\right)\sin(x_{2,1}(t-\tau_2)) + \\ \dfrac{kr}{2J_2}(l-b) + \dfrac{kr^2}{4J_2}\sin(x_{1,1}(t-\tau_1)). \end{cases}$$

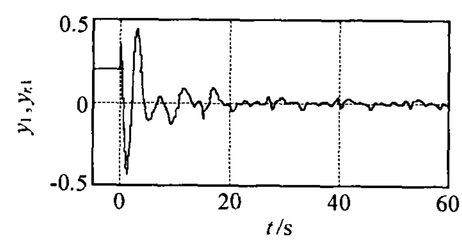
其中: 假设 $J_1 = J_2 = 1$; 未知参数为 $m_1 = 2$, $m_2 = 2.5$, $k = 100$, $r = 0.5$, $l = 0.5$, $g = 9.81$, $b = 0.4$, 以上参数的物理意义参见文献[6]; 时滞仍然为 $\tau_1 = 5$, $\tau_2 = 3$; 初始条件保持不变; 参考信号设定为 $y_{r,1}(t) = \sin(t)\sin(0.5t)$, $y_{r,2}(t) = \sin(t)$. 仿真结果如图 2 所示.



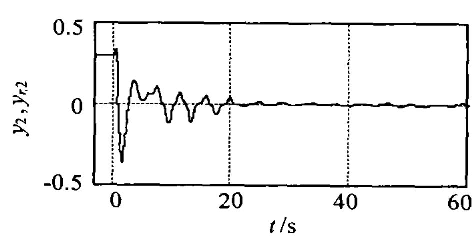
(a)　输出 y_1 和参数信号 $y_{r,1}$



(b)　输出 y_2 和参数信号 $y_{r,2}$



(c)　跟踪误差 $y_1 - y_{r,1}$



(d)　跟踪误差 $y_2 - y_{r,2}$

图 2　大系统 Σ_3-Σ_4 的仿真结果

仿真结果表明, 将设计好的控制器应用于两个动态和参考信号完全不同的大系统时, 都能实现很好的跟踪性能. 这说明所设定的控制器具有较强的泛化能力和自适应能力.

5　结　　语

本文提出了一种神经网络分散跟踪控制方案. 对关联项的假设(例如匹配条件被已知函数所界定等)都被取消. 特别地, 当参考信号为常数时, 所设计的控制器是无记忆的. 仿真结果很好地说明了控制器的泛化能力以及对非线性的适应能力.

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