

拓扑变换下多智能体切换系统的 分布式优化控制

3.1 问题描述

3.1.1 系统描述

考虑一类高阶非线性严格反馈多智能体切换系统如下：

$$\begin{cases} \dot{x}_{i,1}(t) = x_{i,2} + g_{i,1}^{\chi_i(t)}(x_{i,1}) \\ \dot{x}_{i,l}(t) = x_{i,l+1} + g_{i,l}^{\chi_i(t)}(x_{i,1}, x_{i,2}, \dots, x_{i,l}) \\ \dot{x}_{i,n}(t) = u_i(t) + g_{i,n}^{\chi_i(t)}(x_{i,1}, x_{i,2}, \dots, x_{i,n}) \\ y_i(t) = x_{i,1}(t) \end{cases}, \quad i = 1, 2, \dots, N, l = 2, 3, \dots, n-1$$

(3-1)

式中： $u_i(t)$ 为控制输入； $y_i(t)$ 为系统输出， $g_{i,l}^{\chi_i(t)}(x_{i,1}, x_{i,2}, \dots, x_{i,l})$ 为定义在系统状态上的未知非线性函数， $\chi(t)$ 为分段连续函数，用来描述子系统之间切换的触发条件，当 $\chi(t)=q$ 时，意味着第 q 个子系统处在活动状态。

定义第 i 个智能体的系统状态向量 $\mathbf{X}_{i,l} = (x_{i,1}, x_{i,2}, \dots, x_{i,l})^T \in \mathbb{R}^l$ 。将系统式(3-1)改写如下:

$$\begin{cases} \dot{\mathbf{X}}_{i,n} = \mathbf{A}_i \mathbf{X}_{i,n} + \mathbf{K}_i \mathbf{y}_i + \sum_{l=1}^n \mathbf{B}_{i,l} [g_{i,l}^q(\mathbf{X}_{i,l})] + \mathbf{B}_i u_i(t) \\ \mathbf{y}_i = \mathbf{C}_i \mathbf{X}_{i,n} \end{cases} \quad (3-2)$$

式中

$$\mathbf{A}_i = \begin{bmatrix} -k_{i,1} & & & \\ & \ddots & & \\ & & I_{n-1} & \\ -k_{i,n} & 0 & \cdots & 0 \end{bmatrix}, \quad \mathbf{K}_i = \begin{bmatrix} k_{i,1} \\ \vdots \\ k_{i,n} \end{bmatrix}, \quad \mathbf{B}_i = \begin{bmatrix} 0 \\ \vdots \\ 1 \end{bmatrix},$$

$$\mathbf{B}_{i,l} = [0 \cdots 1 \cdots 0]^T, \quad \mathbf{C}_i = [1 \quad 0 \cdots 0]$$

给定一个正定矩阵 $\mathbf{Q}_i^T = \mathbf{Q}_i$, 存在一个正定矩阵 $\mathbf{P}_i^T = \mathbf{P}_i$ 并满足

$$\mathbf{A}_i^T \mathbf{P}_i + \mathbf{P}_i \mathbf{A}_i = -2\mathbf{Q}_i \quad (3-3)$$

3.1.2 构造含惩罚项的优化问题

考虑路径追踪问题的局部目标函数设计如下:

$$\begin{aligned} f_i(x_{i,1}) &= a_i(x_{i,1} - x_d)^2 + c \\ &= a_i x_{i,1}^2 + b_i x_{i,1} + c_i \end{aligned} \quad (3-4)$$

式中: x_d 为智能体追踪的目标信号; $a_i > 0, b_i = -2a_i x_d, c_i = a_i x_d^2 + c, 1 \leq i \leq N$ 且 a_i, c 是常数。定义全局目标函数 $f: \mathbb{R}^N \rightarrow \mathbb{R}$ 为

$$f(\mathbf{x}_1) = \sum_{i=1}^N f_i(x_{i,1}) \quad (3-5)$$

考虑局部目标函数 f_i 是可导的强凸函数, 全局目标函数 f 也是可导的强凸函数。定义向量 $\mathbf{x}_1 = [x_{1,1}, x_{2,1}, \dots, x_{N,1}]^T$ 。根据引理 1.3, 对于某一常数 $\alpha \in \mathbb{R}$, 若有 $\mathbf{x}_1 = \alpha \cdot \mathbf{1}_N$, 则可得

$$\mathbf{L}^{\kappa(t)} \mathbf{x}_1 = 0 \quad (3-6)$$

基于上式, 设计如下惩罚项:

$$\mathbf{x}_1^T \mathbf{L}^{\kappa(t)} \mathbf{x}_1 = 0 \quad (3-7)$$

定义如下惩罚函数:

$$P(\mathbf{x}_1) = \sum_{i=1}^N f_i(x_{i,1}) + \mathbf{x}_1^T \mathbf{L}^{\kappa(t)} \mathbf{x}_1 \quad (3-8)$$

因为全局目标函数是强凸函数,可以得到惩罚函数也是强凸函数的结论。

本章的目标是设计控制器 $(u_1, \dots, u_N)$,来对每个 $i=1, \dots, N$,使得 $\lim_{t \rightarrow \infty} x_{i,1} \rightarrow x_{i,1}^*$ 。定义向量 $\mathbf{x}_1^* = (x_{1,1}^*, \dots, x_{N,1}^*)$,其中第 i 个智能体的分布式优化问题最优解 $x_{1,1}^*$ 定义如下:

$$(x_{1,1}^*, \dots, x_{N,1}^*) = \underset{(x_{1,1}, \dots, x_{N,1})}{\operatorname{argmin}} P(\mathbf{x}_1) \quad (3-9)$$

3.2 自适应神经网络反演控制器设计

3.2.1 神经网络观测器设计

由于系统中的非线性项 $g_{i,l}^q(\mathbf{X}_{i,l})$ 未知,因此有如下假设:

假设 3.1 根据 RBF 神经网络逼近技术,假设未知函数 $g_i^q(\mathbf{X}_i)$ 可以表示为

$$g_i^q(\mathbf{X}_i | \boldsymbol{\theta}_i) = \boldsymbol{\theta}_i^T \boldsymbol{\phi}_i(\mathbf{X}_i), \quad 1 \leq i \leq n \quad (3-10)$$

式中: $\boldsymbol{\theta}_i$ 为理想常数向量; $\boldsymbol{\phi}_i(\mathbf{X}_i)$ 为高斯基函数向量。

设计基于 RBF 神经网络的状态观测器为

$$\begin{aligned} \dot{\hat{\mathbf{X}}}_{i,n} &= \mathbf{A}_i \hat{\mathbf{X}}_{i,n} + \mathbf{K}_i y_i + \sum_{l=1}^n \mathbf{B}_{i,l} [\hat{g}_{i,l}^q(\hat{\mathbf{X}}_{i,l} | \boldsymbol{\theta}_{i,l})] + \mathbf{B}_i u_i(t) \\ \hat{y}_i &= \mathbf{C}_i \hat{\mathbf{X}}_{i,n} \end{aligned} \quad (3-11)$$

式中: $\mathbf{C} = [1 \cdots 0 \cdots 0]$; $\hat{\mathbf{X}}_{i,l} = (\hat{x}_{i,1}, \hat{x}_{i,2}, \dots, \hat{x}_{i,n})^T$ 是 $\mathbf{X}_{i,l} = (x_{i,1}, x_{i,2}, \dots, x_{i,l})^T$ 的估计值。

定义系统的观测误差 $\mathbf{e}_i = \mathbf{X}_{i,n} - \hat{\mathbf{X}}_{i,n}$,根据式(3-2)和式(3-11)可得

$$\dot{\mathbf{e}}_i = \mathbf{A}_i \mathbf{e}_i + \sum_{l=1}^n \mathbf{B}_{i,l} [g_{i,l}^q(\hat{\mathbf{X}}_{i,l}) - \hat{g}_{i,l}^q(\hat{\mathbf{X}}_{i,l} | \boldsymbol{\theta}_{i,l}) + \Delta g_{i,l}^q] \quad (3-12)$$

式中

$$\Delta g_{i,l}^q = g_{i,l}^q(\mathbf{X}_{i,l}) - g_{i,l}^q(\hat{\mathbf{X}}_{i,l})$$

通过 RBF 神经网络逼近技术可得

$$\hat{g}_{i,l}^q(\hat{\mathbf{X}}_{i,l} \mid \boldsymbol{\theta}_{i,l}) = \boldsymbol{\theta}_{i,l}^T \boldsymbol{\varphi}_{i,l}(\hat{\mathbf{X}}_{i,l}) \quad (3-13)$$

定义最优参数向量为

$$\boldsymbol{\theta}_{i,l}^* = \operatorname{argmin}_{\boldsymbol{\theta}_{i,l} \in \boldsymbol{\Omega}_{i,l}} \left[\sup_{\hat{\mathbf{X}}_{i,l} \in \mathbf{U}_{i,l}} | \hat{g}_{i,l}^q(\hat{\mathbf{X}}_{i,l} \mid \boldsymbol{\theta}_{i,l}) - g_{i,l}^q(\hat{\mathbf{X}}_{i,l}) | \right], \quad 1 \leq l \leq n \quad (3-14)$$

式中: $\boldsymbol{\Omega}_i$ 、 $\mathbf{U}_i$ 分别为变量 $\boldsymbol{\theta}_{i,l}$ 、 $\hat{\mathbf{X}}_{i,l}$ 的紧集。

定义最小逼近误差和参数估计误差为

$$\begin{cases} \boldsymbol{\epsilon}_{i,l}^q = g_{i,l}^q(\hat{\mathbf{X}}_{i,l}) - \hat{g}_{i,l}^q(\hat{\mathbf{X}}_{i,l} \mid \boldsymbol{\theta}_{i,l}^*) \\ \tilde{\boldsymbol{\theta}}_{i,l} = \boldsymbol{\theta}_{i,l}^* - \boldsymbol{\theta}_{i,l} \end{cases}, \quad l = 1, 2, \dots, n \quad (3-15)$$

假设 3.2 假设最优逼近误差有界, 存在已知正常数 ϵ_0 , 使得 $|\boldsymbol{\epsilon}_i| \leq \epsilon_0$ 。

假设 3.3 存在一组已知常数 $\gamma_{i,l}$, 使得以下关系成立:

$$|g_{i,l}(\mathbf{X}_{i,l}) - g_{i,l}(\hat{\mathbf{X}}_{i,l})| \leq \gamma_{i,l} \|\mathbf{X}_{i,l} - \hat{\mathbf{X}}_{i,l}\| \quad (3-16)$$

根据式(3-11)和式(3-12)可得

$$\begin{aligned} \dot{\mathbf{e}}_i &= \mathbf{A}_i \mathbf{e}_i + \sum_{l=1}^n \mathbf{B}_{i,l} [g_{i,l}^q(\hat{\mathbf{X}}_{i,l}) - \hat{g}_{i,l}^q(\hat{\mathbf{X}}_{i,l} \mid \boldsymbol{\theta}_{i,l}) + \Delta g_{i,l}^q] \\ &= \mathbf{A}_i \mathbf{e}_i + \sum_{l=1}^n \mathbf{B}_{i,l} [\boldsymbol{\epsilon}_{i,l}^q + \Delta g_{i,l}^q + \tilde{\boldsymbol{\theta}}_{i,l}^T \boldsymbol{\varphi}_{i,l}(\hat{\mathbf{X}}_{i,l})] \\ &= \mathbf{A}_i \mathbf{e}_i + \Delta \mathbf{g}_i^q + \boldsymbol{\epsilon}_i^q + \sum_{l=1}^n \mathbf{B}_{i,l} [\tilde{\boldsymbol{\theta}}_{i,l}^T \boldsymbol{\varphi}_{i,l}(\hat{\mathbf{X}}_{i,l})] \end{aligned} \quad (3-17)$$

式中

$$\boldsymbol{\epsilon}_i^q = [\boldsymbol{\epsilon}_{i,1}^q, \dots, \boldsymbol{\epsilon}_{i,n}^q]^T, \quad \Delta \mathbf{g}_i^q = [\Delta g_{i,1}^q, \dots, \Delta g_{i,n}^q]^T。$$

选取 Lyapunov 函数:

$$V_0 = \sum_{i=1}^N V_{i,0} = \sum_{i=1}^N \frac{1}{2} \mathbf{e}_i^T \mathbf{P}_i \mathbf{e}_i \quad (3-18)$$

对式(3-18)进行微分可得

$$\begin{aligned} \dot{V}_0 &\leq \sum_{i=1}^N \left\{ \frac{1}{2} \mathbf{e}_i^T (\mathbf{P}_i \mathbf{A}_i^T + \mathbf{A}_i \mathbf{P}_i) \mathbf{e}_i + \mathbf{e}_i^T \mathbf{P}_i (\boldsymbol{\epsilon}_i^q + \Delta \mathbf{g}_i^q) + \sum_{l=1}^n \mathbf{e}_i^T \mathbf{P}_i \mathbf{B}_{i,l} [\tilde{\boldsymbol{\theta}}_{i,l}^T \boldsymbol{\varphi}_{i,l}(\hat{\mathbf{X}}_{i,l})] \right\} \\ &\leq \sum_{i=1}^N \left[-\mathbf{e}_i^T \mathbf{Q}_i \mathbf{e}_i + \mathbf{e}_i^T \mathbf{P}_i (\boldsymbol{\epsilon}_i^q + \Delta \mathbf{g}_i^q) + \mathbf{e}_i^T \mathbf{P}_i \sum_{l=1}^n \mathbf{B}_{i,l} \tilde{\boldsymbol{\theta}}_{i,l}^T \boldsymbol{\varphi}_{i,l}(\hat{\mathbf{X}}_{i,l}) \right] \end{aligned} \quad (3-19)$$

通过 Young's 不等式以及假设 3.3 可得

$$\mathbf{e}_i^T \mathbf{P}_i (\boldsymbol{\epsilon}_i^q + \Delta \mathbf{g}_i^q) \leq |\mathbf{e}_i^T \mathbf{P}_i \boldsymbol{\epsilon}_i^q| + |\mathbf{e}_i^T \mathbf{P}_i \Delta \mathbf{g}_i^q|$$

$$\begin{aligned}
&\leq \frac{1}{2} \| \mathbf{e}_i \|^2 + \frac{1}{2} \| \mathbf{P} \boldsymbol{\epsilon}_i^q \|^2 + \frac{1}{2} \| \mathbf{e}_i \|^2 + \frac{1}{2} \| \mathbf{P}_i \|^2 \| \Delta \mathbf{g}_i^q \|^2 \\
&\leq \| \mathbf{e}_i \|^2 + \frac{1}{2} \| \mathbf{P}_i \boldsymbol{\epsilon}_i^q \|^2 + \frac{1}{2} \| \mathbf{P}_i \|^2 \sum_{l=1}^n | \Delta g_{i,l}^q |^2 \\
&\leq \| \mathbf{e}_i \|^2 + \frac{1}{2} \| \mathbf{e}_i \|^2 \| \mathbf{P}_i \|^2 \sum_{l=1}^n \gamma_{i,l}^{q^2} + \frac{1}{2} \| \mathbf{P}_i \boldsymbol{\epsilon}_i^q \|^2 \\
&\leq \| \mathbf{e}_i \|^2 \left(1 + \frac{1}{2} \| \mathbf{P}_i \|^2 \sum_{l=1}^n \gamma_{i,l}^{q^2} \right) + \frac{1}{2} \| \mathbf{P}_i \boldsymbol{\epsilon}_i^q \|^2
\end{aligned} \tag{3-20}$$

以及

$$\begin{aligned}
&\mathbf{e}_i^T \mathbf{P}_i \sum_{l=1}^n \mathbf{B}_{i,l} \tilde{\boldsymbol{\theta}}_{i,l}^T \boldsymbol{\varphi}_{i,l}(\hat{\mathbf{X}}_{i,l}) \\
&\leq \frac{1}{2} \mathbf{e}_i^T \mathbf{P}_i^T \mathbf{P}_i \mathbf{e}_i + \frac{1}{2} \sum_{l=1}^n \tilde{\boldsymbol{\theta}}_{i,l}^T \boldsymbol{\varphi}_{i,l}(\hat{\mathbf{X}}_{i,l}) \boldsymbol{\varphi}_{i,l}^T(\hat{\mathbf{X}}_{i,l}) \tilde{\boldsymbol{\theta}}_{i,l} \\
&\leq \frac{1}{2} \lambda_{i,\max}^2(\mathbf{P}_i) \| \mathbf{e}_i \|^2 + \frac{1}{2} \sum_{l=1}^n \tilde{\boldsymbol{\theta}}_{i,l}^T \tilde{\boldsymbol{\theta}}_{i,l}
\end{aligned} \tag{3-21}$$

式中: $\lambda_{i,\max}(\mathbf{P}_i)$ 为正定矩阵 $\mathbf{P}_i$ 的最大特征值。

根据式(3-19)~式(3-21)可得

$$\dot{V}_0 \leq \sum_{i=1}^N \left(-q_{i,0} \| \mathbf{e}_i \|^2 + \frac{1}{2} \| \mathbf{P}_i \boldsymbol{\epsilon}_i^q \|^2 + \frac{1}{2} \sum_{l=1}^n \tilde{\boldsymbol{\theta}}_{i,l}^T \tilde{\boldsymbol{\theta}}_{i,l} \right) \tag{3-22}$$

式中

$$0 < \boldsymbol{\varphi}_{i,l}(\cdot) \boldsymbol{\varphi}_{i,l}^T(\cdot) \leq 1; q_{i,0} = \lambda_{i,\min}(\mathbf{Q}_i) - \left(1 + \frac{1}{2} \| \mathbf{P}_i \|^2 \sum_{l=1}^n \gamma_{i,l}^2 + \frac{1}{2} \lambda_{i,\max}^2(\mathbf{P}_i) \right)$$

式(3-22)改写为

$$\dot{V}_0 \leq -q_0 \| \mathbf{e} \|^2 + \frac{1}{2} \| \mathbf{P} \boldsymbol{\epsilon} \|^2 + \sum_{i=1}^N \sum_{l=1}^n \frac{1}{2} \tilde{\boldsymbol{\theta}}_{i,l}^T \tilde{\boldsymbol{\theta}}_{i,l} \tag{3-23}$$

式中: $q_0 = \sum_{i=1}^N q_{i,0}$ 。

3.2.2 分布式控制器设计

本节结合自适应反演控制、观测器技术和动态面控制(Dynamic Surface Control, DSC)技术设计虚拟控制律、控制输入和参数自适应律。定义误差变量:

$$\begin{cases} s_{i,1} = x_{i,1} - x_{i,1}^* \\ s_{i,l} = \hat{x}_{i,l} - v_{i,l}, \quad l = 2, \dots, n \\ w_{i,l} = v_{i,l} - x_{i,l}^* \end{cases} \quad (3-24)$$

式中: $s_{i,l}$ 为误差面; $v_{i,l}$ 为滤波器输出; $x_{i,l}^*$ 为虚拟控制律; w_i 为 $v_{i,l}$ 和 $x_{i,l}^*$ 的误差。

第 1 步 计算惩罚函数式(3-8)的梯度值:

$$\frac{\partial P(\mathbf{x}_1)}{\partial \mathbf{x}_1} = \text{vec}\left(\frac{\partial f_i(x_{i,1}(t))}{\partial x_{i,1}}\right) + \mathbf{L}^{\kappa(t)} \mathbf{x}_1 \quad (3-25)$$

式中: $\text{vec}\left(\frac{\partial f_i(x_{i,1}(t))}{\partial x_{i,1}}\right)$ 为元素 $\frac{\partial f_i(x_{i,1}(t))}{\partial x_{i,1}}$ 的列向量。

由于惩罚函数 $P(\mathbf{x}_1)$ 是一个强凸函数,那么可以得到分布式优化问题的最优解满足如下形式:

$$\frac{\partial P(\mathbf{x}_1^*)}{\partial \mathbf{x}_1^*} = 0 \quad (3-26)$$

根据式(3-8)和式(3-26)可得

$$\frac{\partial f_i(x_{i,1}^*(t))}{\partial x_{i,1}^*} + \sum_{j \in N_i} a_{ij}(x_{i,1}^* - x_{j,1}^*) = 0 \quad (3-27)$$

由式(3-4)和式(3-27)可得

$$2a_i(x_{i,1}^* - x_d) + \sum_{j \in N_i} a_{ij}(x_{i,1}^* - x_{j,1}^*) = 0 \quad (3-28)$$

根据式(3-24)和式(3-28)可得

$$\begin{aligned} \frac{\partial P(\mathbf{x}_1)}{\partial x_{i,1}} &= \frac{\partial f_i(x_{i,1}(t))}{\partial x_{i,1}} + \sum_{j \in N_i} a_{ij}(x_{i,1} - x_{j,1}) \\ &= 2a_i(x_{i,1} - x_d) + \sum_{j \in N_i} a_{ij}(x_{i,1} - x_{j,1}) \\ &= 2a_i(x_{i,1} - x_d) + \sum_{j \in N_i} a_{ij}(x_{i,1} - x_{j,1}) - 2a_i(x_{i,1}^* - x_d) + \sum_{j \in N_i} a_{ij}(x_{i,1}^* - x_{j,1}^*) \\ &= 2a_i s_{i,1} + \sum_{j \in N_i} a_{ij}(s_{i,1} - s_{j,1}) \end{aligned} \quad (3-29)$$

取 $\mathbf{s}_1 = [s_{1,1}, \dots, s_{N,1}]^T$, 根据式(3-29)可得

$$\frac{\partial P(\mathbf{x}_1)}{\partial \mathbf{x}_1} = \mathbf{H}^{\kappa(t)} \mathbf{s}_1 \quad (3-30)$$

式中: $\mathbf{H}^{\kappa(t)} = \mathbf{A} + \mathbf{L}^{\kappa(t)}$; $\mathbf{A} = \text{diag}\{2a_i\}$ 。

构造 Lyapunov 函数:

$$\begin{aligned} V_1 &= V_0 + \frac{1}{2} \left(\frac{\partial P(\mathbf{x}_1)}{\partial \mathbf{x}_1} \right)^T \mathbf{H}^{\kappa(t)-1} \left(\frac{\partial P(\mathbf{x}_1)}{\partial \mathbf{x}_1} \right) + \sum_{i=1}^N \frac{1}{\sigma_{i,1}} \tilde{\boldsymbol{\theta}}_{i,1}^T \tilde{\boldsymbol{\theta}}_{i,1} \\ &= V_0 + \frac{1}{2} \mathbf{s}_1^T \mathbf{H}^{\kappa(t)} \mathbf{s}_1 + \sum_{i=1}^N \frac{1}{\sigma_{i,1}} \tilde{\boldsymbol{\theta}}_{i,1}^T \tilde{\boldsymbol{\theta}}_{i,1} \end{aligned} \quad (3-31)$$

式中: $\sigma_{i,1}$ 为设计参数。

根据式(3-1)、式(3-11)和式(3-24)可得

$$\dot{\mathbf{s}}_{i,1} = \hat{\mathbf{x}}_{i,2} + \boldsymbol{\theta}_{i,1}^T \boldsymbol{\varphi}_{i,1} + \tilde{\boldsymbol{\theta}}_{i,1}^T \boldsymbol{\varphi}_{i,1} + \Delta \mathbf{g}_{i,1}^q + \boldsymbol{\epsilon}_{i,1}^q + \mathbf{e}_{i,2} \quad (3-32)$$

由式(3-31)和式(3-32)可得

$$\begin{aligned} \dot{V}_1 &= \dot{V}_0 + \mathbf{s}_1^T \mathbf{H}^{\kappa(t)} \dot{\mathbf{s}}_1 + \sum_{i=1}^N \frac{1}{\sigma_{i,1}} \tilde{\boldsymbol{\theta}}_{i,1}^T \dot{\tilde{\boldsymbol{\theta}}}_{i,1} \\ &= \dot{V}_0 + \mathbf{s}_1^T \mathbf{H}^{\kappa(t)} (\hat{\mathbf{x}}_2 + \text{vec}(\boldsymbol{\theta}_{i,1}^T \boldsymbol{\varphi}_{i,1}) + \text{vec}(\tilde{\boldsymbol{\theta}}_{i,1}^T \boldsymbol{\varphi}_{i,1}) + \Delta \mathbf{g}_1^q + \boldsymbol{\epsilon}_1^q + \mathbf{e}_2) + \\ &\quad \sum_{i=1}^N \frac{1}{\sigma_{i,1}} \tilde{\boldsymbol{\theta}}_{i,1}^T \dot{\tilde{\boldsymbol{\theta}}}_{i,1} \\ &= \dot{V}_0 + \mathbf{s}_1^T \mathbf{H}^{\kappa(t)} (\mathbf{s}_2 + \mathbf{w}_2 + \mathbf{x}_2^* + \text{vec}(\boldsymbol{\theta}_{i,1}^T \boldsymbol{\varphi}_{i,1}) + \text{vec}(\tilde{\boldsymbol{\theta}}_{i,1}^T \boldsymbol{\varphi}_{i,1}) + \Delta \mathbf{g}_1^q + \boldsymbol{\epsilon}_1^q + \mathbf{e}_2) + \\ &\quad \sum_{i=1}^N \frac{1}{\sigma_{i,1}} \tilde{\boldsymbol{\theta}}_{i,1}^T \dot{\tilde{\boldsymbol{\theta}}}_{i,1} \\ &= \dot{V}_0 + \mathbf{s}_1^T \mathbf{H}^{\kappa(t)} \mathbf{s}_2 + \mathbf{s}_1^T \mathbf{H}^{\kappa(t)} \mathbf{w}_2 + \mathbf{s}_1^T \mathbf{H}^{\kappa(t)} (\mathbf{x}_2^* + \text{vec}(\boldsymbol{\theta}_{i,1}^T \boldsymbol{\varphi}_{i,1}) + \text{vec}(\tilde{\boldsymbol{\theta}}_{i,1}^T \boldsymbol{\varphi}_{i,1})) + \\ &\quad \mathbf{s}_1^T \mathbf{H}^{\kappa(t)} \Delta \mathbf{g}_1^q + \mathbf{s}_1^T \mathbf{H}^{\kappa(t)} \boldsymbol{\epsilon}_1^q + \mathbf{s}_1^T \mathbf{H}^{\kappa(t)} \mathbf{e}_2 - \sum_{i=1}^N \frac{1}{\sigma_{i,1}} \tilde{\boldsymbol{\theta}}_{i,1}^T \dot{\tilde{\boldsymbol{\theta}}}_{i,1} \end{aligned} \quad (3-33)$$

式中: $\mathbf{s}_2 = [s_{1,2}, s_{2,2}, \dots, s_{N,2}]^T$; $\mathbf{w}_2 = [w_{1,2}, w_{2,2}, \dots, w_{N,2}]^T$; $\mathbf{x}_2^* = [x_{1,2}^*, x_{2,2}^*, \dots, x_{N,2}^*]^T$; $\Delta \mathbf{g}_1^q = [\Delta g_{1,1}^q, \Delta g_{2,1}^q, \dots, \Delta g_{N,1}^q]^T$; $\boldsymbol{\epsilon}_1^q = [\epsilon_{1,1}^q, \epsilon_{2,1}^q, \dots, \epsilon_{N,1}^q]^T$; $\mathbf{e}_2 = [e_{1,2}, e_{2,2}, \dots, e_{N,2}]^T$; $\text{vec}(\boldsymbol{\theta}_{i,1}^T \boldsymbol{\varphi}_{i,1})$ 和 $\text{vec}(\tilde{\boldsymbol{\theta}}_{i,1}^T \boldsymbol{\varphi}_{i,1})$ 为列向量。

根据 Young's 不等式可得

$$\mathbf{s}_1^T \mathbf{H}^{\kappa(t)} \mathbf{s}_2 \leq \frac{1}{2} \mathbf{s}_1^T \mathbf{H}^{\kappa(t)} \mathbf{H}^{\kappa(t)T} \mathbf{s}_1 + \frac{1}{2} \mathbf{s}_2^T \mathbf{s}_2 \quad (3-34)$$

$$\mathbf{s}_1^T \mathbf{H}^{\kappa(t)} \mathbf{w}_2 \leq \frac{1}{2} \mathbf{s}_1^T \mathbf{H}^{\kappa(t)} \mathbf{H}^{\kappa(t)T} \mathbf{s}_1 + \frac{1}{2} \mathbf{w}_2^T \mathbf{w}_2 \quad (3-35)$$

$$\mathbf{s}_1^T \mathbf{H}^{\kappa(t)} \Delta \mathbf{g}_1^q \leq \frac{1}{2} \mathbf{s}_1^T \mathbf{H}^{\kappa(t)} \boldsymbol{\gamma}_1^q \boldsymbol{\gamma}_1^{qT} \mathbf{H}^{\kappa(t)T} \mathbf{s}_1 + \frac{1}{2} \mathbf{e}_1^T \mathbf{e}_1 \quad (3-36)$$

$$\mathbf{s}_1^T \mathbf{H}^{\kappa(t)} \boldsymbol{\epsilon}_1^q \leq \frac{1}{2} \mathbf{s}_1^T \mathbf{H}^{\kappa(t)} \mathbf{H}^{\kappa(t)T} \mathbf{s}_1 + \frac{1}{2} \boldsymbol{\epsilon}_1^{qT} \boldsymbol{\epsilon}_1^q \quad (3-37)$$

$$\mathbf{s}_1^T \mathbf{H}^{\kappa(t)} \mathbf{e}_2 \leq \frac{1}{2} \mathbf{s}_1^T \mathbf{H}^{\kappa(t)} \mathbf{H}^{\kappa(t)T} \mathbf{s}_1 + \frac{1}{2} \mathbf{e}_2^T \mathbf{e}_2 \quad (3-38)$$

式中: $\boldsymbol{\gamma}_1^q = \text{diag}[\boldsymbol{\gamma}_{i,1}^q]$; $\mathbf{e}_1 = [e_{1,1}, e_{2,1}, \dots, e_{N,1}]^T$ 。

将式(3-34)~式(3-38)代入式(3-33)可得

$$\begin{aligned} \dot{V}_1 &\leq \dot{V}_0 + \mathbf{s}_1^T \mathbf{H}^{\kappa(t)} (\mathbf{x}_2^* + \text{vec}(\boldsymbol{\theta}_{i,1}^T \boldsymbol{\varphi}_{i,1}) + \text{vec}(\tilde{\boldsymbol{\theta}}_{i,1}^T \boldsymbol{\varphi}_{i,1})) + \\ &\quad \frac{1}{2} \mathbf{s}_1^T \mathbf{H}^{\kappa(t)} \mathbf{H}^{\kappa(t)T} \mathbf{s}_1 + \frac{1}{2} \mathbf{w}_2^T \mathbf{w}_2 + \frac{1}{2} \mathbf{s}_1^T \mathbf{H}^{\kappa(t)} \mathbf{H}^{\kappa(t)T} \mathbf{s}_1 + \frac{1}{2} \mathbf{s}_2^T \mathbf{s}_2 + \\ &\quad \frac{1}{2} \mathbf{s}_1^T \mathbf{H}^{\kappa(t)} \boldsymbol{\gamma}_1^q \boldsymbol{\gamma}_1^{qT} \mathbf{H}^{\kappa(t)T} \mathbf{s}_1 + \frac{1}{2} \mathbf{e}_1^T \mathbf{e}_1 + \frac{1}{2} \mathbf{s}_1^T \mathbf{H}^{\kappa(t)} \mathbf{H}^{\kappa(t)T} \mathbf{s}_1 + \frac{1}{2} \boldsymbol{\epsilon}_1^{qT} \boldsymbol{\epsilon}_1^q + \\ &\quad \frac{1}{2} \mathbf{s}_1^T \mathbf{H}^{\kappa(t)} \mathbf{H}^{\kappa(t)T} \mathbf{s}_1 + \frac{1}{2} \mathbf{e}_2^T \mathbf{e}_2 - \sum_{i=1}^N \frac{1}{\sigma_{i,1}} \tilde{\boldsymbol{\theta}}_{i,1}^T \dot{\boldsymbol{\theta}}_{i,1} \end{aligned} \quad (3-39)$$

与第2章相同,可得如下等式:

$$\mathbf{s}_1^T \mathbf{H} \mathbf{H}^T \mathbf{s}_1 = \sum_{i=1}^N [2a_i (x_{i,1} - x_d) + \sum_{j \in N_i} a_{ij} (x_{i,1} - x_{j,1})]^2 \quad (3-40)$$

$$\mathbf{s}_1^T \mathbf{H} \boldsymbol{\gamma}_1 \boldsymbol{\gamma}_1^T \mathbf{H}^T \mathbf{s}_1 = \sum_{i=1}^N \boldsymbol{\gamma}_{i,1}^2 [2a_i (x_{i,1} - x_d) + \sum_{j \in N_i} a_{ij} (x_{i,1} - x_{j,1})]^2 \quad (3-41)$$

根据式(3-39)~式(3-41),设计第1步虚拟控制律 $x_{i,2}^*$ 和自适应律 $\boldsymbol{\theta}_{i,1}$:

$$x_{i,2}^* = -c_{i,1} [2a_i (x_{i,1} - x_d) + \sum_{j \in N_i} a_{ij} (x_{i,1} - x_{j,1})] - \boldsymbol{\theta}_{i,1}^T \boldsymbol{\varphi}_{i,1} (\hat{\mathbf{X}}_{i,1}) \quad (3-42)$$

$$\dot{\boldsymbol{\theta}}_{i,1} = \sigma_{i,1} \boldsymbol{\varphi}_{i,1} (\hat{\mathbf{X}}_{i,1}) [2a_i (x_{i,1} - x_d) + \sum_{j \in N_i} a_{ij} (x_{i,1} - x_{j,1})] - \rho_{i,1} \boldsymbol{\theta}_{i,1} \quad (3-43)$$

式中: $c_{i,1} = \frac{5}{2} + \frac{\boldsymbol{\gamma}_{i,1}^{q2}}{2}$ 和 $\rho_{i,1}$ 为设计参数。

将式(3-42)和式(3-43)代入式(3-39)可得

$$\begin{aligned} \dot{V}_1 &\leq -q_0 \|\mathbf{e}\|^2 + \frac{1}{2} \|\mathbf{P}\boldsymbol{\epsilon}\|^2 + \sum_{i=1}^N \sum_{l=1}^n \frac{1}{2} \tilde{\boldsymbol{\theta}}_{i,l}^T \tilde{\boldsymbol{\theta}}_{i,l} - \frac{1}{2} \mathbf{s}_1^T \mathbf{H}^{\kappa(t)} \mathbf{H}^{\kappa(t)T} \mathbf{s}_1 + \\ &\quad \frac{1}{2} \mathbf{e}_2^T \mathbf{e}_2 + \frac{1}{2} \mathbf{e}_1^T \mathbf{e}_1 + \frac{1}{2} \boldsymbol{\epsilon}_1^{qT} \boldsymbol{\epsilon}_1^q + \sum_{i=1}^N \frac{\rho_{i,1}}{\sigma_{i,1}} \tilde{\boldsymbol{\theta}}_{i,1}^T \boldsymbol{\theta}_{i,1} + \frac{1}{2} \mathbf{s}_2^T \mathbf{s}_2 + \frac{1}{2} \mathbf{w}_2^T \mathbf{w}_2 \end{aligned} \quad (3-44)$$

式中

$$q_1 = q_0 - N; \quad \eta_1 = \frac{1}{2} \|\mathbf{P}\boldsymbol{\epsilon}\|^2 + \frac{1}{2} \boldsymbol{\epsilon}_1^{qT} \boldsymbol{\epsilon}_1^q$$

通过使用滤波器技术可以获得状态变量 $v_{i,2}$ 为

$$\lambda_{i,2} \dot{v}_{i,2} + v_{i,2} = x_{i,2}^*, \quad v_{i,2}(0) = x_{i,2}^*(0) \quad (3-45)$$

进一步,由式(3-24)和式(3-45)可得

$$\dot{w}_{i,2} = \dot{v}_{i,2} - \dot{x}_{i,2}^* = -\frac{v_{i,2} - x_{i,2}^*}{\lambda_{i,2}} - \dot{x}_{i,2}^* = -\frac{w_{i,2}}{\lambda_{i,2}} + B_{i,2} \quad (3-46)$$

式中: $\lambda_{i,2}$ 为设计参数; $B_{i,2} = -\dot{x}_{i,2}^*$, 根据相关文献可知, 存在一个正整数 $M_{i,2}$, 使得 $|B_{i,2}| \leq M_{i,2}$ 。

第2步 定义误差变量 $s_{i,2} = \hat{x}_{i,2} - v_{i,2}$, 进一步可得

$$\begin{aligned} \dot{s}_{i,2} &= \dot{\hat{x}}_{i,2} - \dot{v}_{i,2} \\ &= \hat{x}_{i,3} + k_{i,2} e_{i,1} + \boldsymbol{\theta}_{i,2}^T \boldsymbol{\varphi}_{i,2} + \tilde{\boldsymbol{\theta}}_{i,2}^T \boldsymbol{\varphi}_{i,2} + \boldsymbol{\epsilon}_{i,2}^q + \Delta g_{i,2}^q - \dot{v}_{i,2} \\ &= s_{i,3} + w_{i,3} + x_{i,3}^* + k_{i,2} e_{i,1} + \boldsymbol{\theta}_{i,2}^T \boldsymbol{\varphi}_{i,2} + \tilde{\boldsymbol{\theta}}_{i,2}^T \boldsymbol{\varphi}_{i,2} + \boldsymbol{\epsilon}_{i,2}^q + \Delta g_{i,2}^q - \dot{v}_{i,2} \end{aligned} \quad (3-47)$$

构造 Lyapunov 函数:

$$V_2 = V_1 + \sum_{i=1}^N V_{i,2} = V_1 + \frac{1}{2} \sum_{i=1}^N \{s_{i,2}^2 + \frac{1}{\sigma_{i,2}} \tilde{\boldsymbol{\theta}}_{i,2}^T \tilde{\boldsymbol{\theta}}_{i,2} + w_{i,2}^2\} \quad (3-48)$$

根据 Young's 不等式可得

$$s_{i,2} k_{i,2} e_{i,1} \leq \frac{1}{2} s_{i,2}^2 + \frac{1}{2} k_{i,2}^2 \|e_{i,1}\|^2 \quad (3-49)$$

$$s_{i,2} (s_{i,3} + w_{i,3}) \leq s_{i,2}^2 + \frac{1}{2} (s_{i,3}^2 + w_{i,3}^2) \quad (3-50)$$

将式(3-49)、式(3-50)代入式(3-48)可得

$$\begin{aligned} \dot{V}_2 &\leq \dot{V}_1 + \sum_{i=1}^N \left[s_{i,2} (x_{i,3}^* + \boldsymbol{\theta}_{i,2}^T \boldsymbol{\varphi}_{i,2} + \tilde{\boldsymbol{\theta}}_{i,2}^T \boldsymbol{\varphi}_{i,2} - \dot{v}_{i,2}) + \frac{5}{2} s_{i,2}^2 + \frac{1}{2} (s_{i,3}^2 + w_{i,3}^2) + \right. \\ &\quad \left. \frac{1}{2} k_{i,2}^2 \|e_{i,1}\|^2 + \frac{1}{2} \|\boldsymbol{\epsilon}_{i,2}^q\|^2 + \frac{1}{2} \gamma_{i,2}^2 \|e_{i,2}\|^2 - \frac{1}{\sigma_{i,2}} \tilde{\boldsymbol{\theta}}_{i,2}^T \dot{\tilde{\boldsymbol{\theta}}}_{i,2} + w_{i,2} \dot{w}_{i,2} \right] \end{aligned} \quad (3-51)$$

设计第2步虚拟控制律和自适应律如下:

$$x_{i,3}^* = -c_{i,2} s_{i,2} - 3s_{i,2} - \boldsymbol{\theta}_{i,2}^T \boldsymbol{\varphi}_{i,2} (\hat{\mathbf{X}}_{i,2}) + \frac{x_{i,2}^* - v_{i,2}}{\lambda_{i,2}} \quad (3-52)$$

$$\dot{\theta}_{i,2} = \sigma_{i,2} \varphi_{i,2}(\hat{\mathbf{X}}_{i,2}) s_{i,2} - \rho_{i,2} \theta_{i,2} \quad (3-53)$$

式中: $\rho_{i,2}$ 为设计参数。

将式(3-52)、式(3-53)和式(3-44)代入式(3-51)可得

$$\begin{aligned} \dot{V}_2 \leq & -q_1 \|\mathbf{e}\|^2 + \eta_1 + \sum_{i=1}^N \sum_{l=1}^n \frac{1}{2} \tilde{\theta}_{i,l}^T \tilde{\theta}_{i,l} + \\ & \sum_{i=1}^N \frac{\rho_{i,1}}{\sigma_{i,1}} \tilde{\theta}_{i,1}^T \theta_{i,1} - \frac{1}{2\lambda_{\max}(\mathbf{H}^{\kappa(t)-1})} \left(\frac{\partial P(\mathbf{x}_1)}{\partial \mathbf{x}_1} \right)^T \mathbf{H}^{\kappa(t)-1} \left(\frac{\partial P(\mathbf{x}_1)}{\partial \mathbf{x}_1} \right) + \\ & \sum_{i=1}^N \frac{1}{2} s_{i,2}^2 + \sum_{i=1}^N \frac{1}{2} w_{i,2}^2 + \sum_{i=1}^N \left[s_{i,2} \left(-c_{i,2} s_{i,2} - 3s_{i,2} - \theta_{i,2}^T \varphi_{i,2}(\hat{\mathbf{X}}_{i,2}) + \right. \right. \\ & \left. \left. \frac{x_{i,2}^* - v_{i,2}}{\lambda_{i,2}} + \theta_{i,2}^T \varphi_{i,2} + \tilde{\theta}_{i,2}^T \varphi_{i,2} - \dot{v}_{i,2} \right) + \right. \\ & \left. \frac{5}{2} s_{i,2}^2 + \frac{1}{2} (s_{i,3}^2 + w_{i,3}^2) + \frac{1}{2} k_{i,2}^2 \|\mathbf{e}_{i,1}\|^2 + \frac{1}{2} \|\boldsymbol{\varepsilon}_{i,2}^q\|^2 + \frac{1}{2} \gamma_{i,2}^{q2} \|\mathbf{e}_{i,2}\|^2 - \right. \\ & \left. \left. \frac{1}{\sigma_{i,2}} \tilde{\theta}_{i,2}^T (\sigma_{i,2} \varphi_{i,2}(\hat{\mathbf{X}}_{i,2}) s_{i,2} - \rho_{i,2} \theta_{i,2}) + w_{i,2} \left(-\frac{w_{i,2}}{\lambda_{i,2}} + B_{i,2} \right) \right] \end{aligned} \quad (3-54)$$

根据 Young's 不等式, $w_{i,2} B_{i,2} \leq \frac{1}{2} w_{i,2}^2 + \frac{1}{2} M_{i,2}^2$ 成立, 由此可得

$$\begin{aligned} \dot{V}_2 \leq & -q_2 \|\mathbf{e}\|^2 + \eta_2 + \sum_{i=1}^N \sum_{l=1}^n \frac{1}{2} \tilde{\theta}_{i,l}^T \tilde{\theta}_{i,l} - \\ & \frac{1}{2\lambda_{\max}(\mathbf{H}^{\kappa(t)-1})} \left(\frac{\partial P(\mathbf{x}_1)}{\partial \mathbf{x}_1} \right)^T \mathbf{H}^{\kappa(t)-1} \left(\frac{\partial P(\mathbf{x}_1)}{\partial \mathbf{x}_1} \right) + \sum_{i=1}^N \frac{\rho_{i,1}}{\sigma_{i,1}} \tilde{\theta}_{i,1}^T \theta_{i,1} + \\ & \sum_{i=1}^N \frac{\rho_{i,2}}{\sigma_{i,2}} \tilde{\theta}_{i,2}^T \theta_{i,2} - \sum_{i=1}^N c_{i,2} s_{i,2}^2 - \sum_{i=1}^N \left(\frac{1}{\lambda_{i,2}} - 1 \right) w_{i,2}^2 + \\ & \sum_{i=1}^N \left[\frac{1}{2} M_{i,2}^2 + \frac{1}{2} (s_{i,3}^2 + w_{i,3}^2) \right] \end{aligned} \quad (3-55)$$

式中

$$q_2 = q_1 - \frac{1}{2} \sum_{i=1}^N (k_{i,2}^2 + \gamma_{i,2}^{q2}) \quad (3-56)$$

$$\eta_2 = \eta_1 + \frac{1}{2} \sum_{i=1}^N \|\boldsymbol{\varepsilon}_{i,2}^q\|^2 \quad (3-57)$$

使用滤波器技术可以获得状态变量 $v_{i,2}$ 为

$$\lambda_{i,3} \dot{v}_{i,3} + v_{i,3} = x_{i,3}^*, \quad v_{i,3}(0) = x_{i,3}^*(0) \quad (3-58)$$

进一步,由式(3-26)和式(3-58)可得

$$\dot{w}_{i,3} = \dot{v}_{i,3} - \dot{x}_{i,3}^* = -\frac{v_{i,3} - x_{i,3}^*}{\lambda_{i,3}} - \dot{x}_{i,3}^* = -\frac{w_{i,3}}{\lambda_{i,3}} + B_{i,3} \quad (3-59)$$

式中: $\lambda_{i,3}$ 为设计参数; $B_{i,3} = -\dot{x}_{i,3}^*$, 存在一个正整数 $M_{i,3}$, 使得 $|B_{i,3}| \leq M_{i,3}$ 。

第 m 步 定义误差变量 $s_{i,m} = \hat{x}_{i,m} - v_{i,m}$, 其导数为

$$\begin{aligned} \dot{s}_{i,m} &= \dot{\hat{x}}_{i,m} - \dot{v}_{i,m} \\ &= \hat{x}_{i,m+1} + k_{i,m} e_{i,1} + \theta_{i,m}^T \varphi_{i,m} + \tilde{\theta}_{i,m}^T \varphi_{i,m} + \epsilon_{i,m}^q + \Delta g_{i,m}^q - \dot{v}_{i,m} \\ &= s_{i,m+1} + w_{i,m+1} + x_{i,m+1}^* + k_{i,m} e_{i,1} + \theta_{i,m}^T \varphi_{i,m} + \tilde{\theta}_{i,m}^T \varphi_{i,m} + \epsilon_{i,m}^q + \Delta g_{i,m}^q - \dot{v}_{i,m} \end{aligned} \quad (3-60)$$

构造 Lyapunov 函数:

$$V_m = V_{m-1} + \sum_{i=1}^N V_{i,m} = V_{m-1} + \frac{1}{2} \sum_{i=1}^N \left\{ s_{i,m}^2 + \frac{1}{\sigma_{i,m}} \tilde{\theta}_{i,m}^T \tilde{\theta}_{i,m} + w_{i,m}^2 \right\} \quad (3-61)$$

式中: $\sigma_{i,m}$ 为设计参数。

对 Lyapunov 函数求导可得

$$\dot{V}_m = \dot{V}_{m-1} + \sum_{i=1}^N \left\{ s_{i,m} \dot{s}_{i,m} + \frac{1}{\sigma_{i,m}} \tilde{\theta}_{i,m}^T \dot{\tilde{\theta}}_{i,m} + w_{i,m} \dot{w}_{i,m} \right\} \quad (3-62)$$

将式(3-60)代入式(3-62)可得

$$\begin{aligned} \dot{V}_m &= \dot{V}_{m-1} + \sum_{i=1}^N [s_{i,m} (s_{i,m+1} + w_{i,m+1} + x_{i,m+1}^* + k_{i,m} e_{i,1} + \theta_{i,m}^T \varphi_{i,m} + \tilde{\theta}_{i,m}^T \varphi_{i,m} + \\ &\quad \epsilon_{i,m}^q + \Delta g_{i,m}^q - \dot{v}_{i,m}) + \frac{1}{\sigma_{i,m}} \tilde{\theta}_{i,m}^T \dot{\tilde{\theta}}_{i,m} + w_{i,m} \dot{w}_{i,m}] \end{aligned} \quad (3-63)$$

根据 Young's 不等式可得

$$s_{i,m} k_{i,m} e_{i,1} \leq \frac{1}{2} s_{i,m}^2 + \frac{1}{2} k_{i,m}^2 \|e_{i,1}\|^2 \quad (3-64)$$

$$s_{i,m} (s_{i,m+1} + w_{i,m+1}) \leq s_{i,m}^2 + \frac{1}{2} (s_{i,m+1}^2 + w_{i,m+1}^2) \quad (3-65)$$

$$s_{i,m} \epsilon_{i,m}^q \leq \frac{1}{2} s_{i,m}^2 + \frac{1}{2} \|\epsilon_{i,m}^q\|^2 \quad (3-66)$$

$$s_{i,m} \Delta g_{i,m}^q \leq \frac{1}{2} s_{i,m}^2 + \frac{1}{2} \gamma_{i,m}^{q2} \|e_{i,m}\|^2 \quad (3-67)$$

将式(3-64)~式(3-67)代入式(3-63)可得

$$\begin{aligned} \dot{V}_m \leq & \dot{V}_{m-1} + \sum_{i=1}^N \left[s_{i,m} (x_{i,m+1}^* + \theta_{i,m}^T \varphi_{i,m} + \tilde{\theta}_{i,m}^T \varphi_{i,m} - \dot{v}_{i,m}) + \frac{5}{2} s_{i,m}^2 + \right. \\ & \frac{1}{2} (s_{i,m+1}^2 + w_{i,m+1}^2) + \frac{1}{2} k_{i,m}^2 \|e_{i,1}\|^2 + \frac{1}{2} \|\epsilon_{i,m}^q\|^2 + \\ & \left. \frac{1}{2} \gamma_{i,m}^{q2} \|e_{i,m}\|^2 - \frac{1}{\sigma_{i,m}} \tilde{\theta}_{i,m}^T \dot{\theta}_{i,m} + w_{i,m} \dot{w}_{i,m} \right] \end{aligned} \quad (3-68)$$

设计第 m 步虚拟控制律和自适应律如下:

$$x_{i,m+1}^* = -c_{i,m} s_{i,m} - 3s_{i,m} - \theta_{i,m}^T \varphi_{i,m} (\hat{X}_{i,m}) + \frac{x_{i,m}^* - v_{i,m}}{\lambda_{i,m}} \quad (3-69)$$

$$\dot{\theta}_{i,m} = \sigma_{i,m} \varphi_{i,m} (\hat{X}_{i,m}) s_{i,m} - \rho_{i,m} \theta_{i,m} \quad (3-70)$$

式中: $\rho_{i,m}$ 为设计参数。

使用滤波器技术可以获得状态变量 $v_{i,m}$ 为

$$\lambda_{i,m} \dot{v}_{i,m} + v_{i,m} = x_{i,m}^*, \quad v_{i,m}(0) = x_{i,m}^*(0) \quad (3-71)$$

进一步,由式(3-26)和式(3-71)可得

$$\dot{w}_{i,m} = \dot{v}_{i,m} - \dot{x}_{i,m}^* = -\frac{v_{i,m} - x_{i,m}^*}{\lambda_{i,m}} - \dot{x}_{i,m}^* = -\frac{w_{i,m}}{\lambda_{i,m}} + B_{i,m} \quad (3-72)$$

式中: $\lambda_{i,m}$ 为设计参数; $B_{i,m} = -\dot{x}_{i,m}^*$, 存在一个正整数 $M_{i,m}$, 使得 $|B_{i,m}| \leq M_{i,m}$ 。

将式(3-69)、式(3-70)和式(3-72)代入式(3-68)可得

$$\begin{aligned} \dot{V}_m \leq & \dot{V}_{m-1} + \sum_{i=1}^N \left[s_{i,m} (-c_{i,m} s_{i,m} - 3s_{i,m} - \theta_{i,m}^T \varphi_{i,m} (\hat{X}_{i,m}) + \frac{x_{i,m}^* - v_{i,m}}{\lambda_{i,m}} + \right. \\ & \theta_{i,m}^T \varphi_{i,m} + \tilde{\theta}_{i,m}^T \varphi_{i,m} - \dot{v}_{i,m}) + \frac{5}{2} s_{i,m}^2 + \frac{1}{2} (s_{i,m+1}^2 + w_{i,m+1}^2) + \frac{1}{2} k_{i,m}^2 \|e_{i,1}\|^2 + \\ & \frac{1}{2} \|\epsilon_{i,m}^q\|^2 + \frac{1}{2} \gamma_{i,m}^{q2} \|e_{i,m}\|^2 - \frac{1}{\sigma_{i,m}} \tilde{\theta}_{i,m}^T (\sigma_{i,m} \varphi_{i,m} (\hat{X}_{i,m}) s_{i,m} - \rho_{i,m} \theta_{i,m}) + \\ & \left. w_{i,m} \left(-\frac{w_{i,m}}{\lambda_{i,m}} + B_{i,m} \right) \right] \end{aligned} \quad (3-73)$$

根据 Young's 不等式, $w_{i,m} B_{i,m} \leq \frac{1}{2} w_{i,m}^2 + \frac{1}{2} M_{i,m}^2$ 成立, 由此可得

$$\dot{V}_m \leq \dot{V}_{m-1} + \sum_{i=1}^N \left[s_{i,m} (-c_{i,m} s_{i,m} - 3s_{i,m} - \theta_{i,m}^T \varphi_{i,m} + \frac{x_{i,m}^* - v_{i,m}}{\lambda_{i,m}} + \theta_{i,m}^T \varphi_{i,m} + \right.$$

$$\begin{aligned}
& \tilde{\boldsymbol{\theta}}_{i,m}^T \boldsymbol{\varphi}_{i,m} - \dot{v}_{i,m}) + \frac{5}{2} s_{i,m}^2 + \frac{1}{2} (s_{i,m+1}^2 + w_{i,m+1}^2) + \frac{1}{2} k_{i,m}^2 \|e_{i,1}\|^2 + \\
& \frac{1}{2} \|\boldsymbol{\epsilon}_{i,m}^q\|^2 + \frac{1}{2} \gamma_{i,m}^{q2} \|e_{i,m}\|^2 - \frac{1}{\sigma_{i,m}} \tilde{\boldsymbol{\theta}}_{i,m}^T (\sigma_{i,m} \boldsymbol{\varphi}_{i,m} s_{i,m} - \rho_{i,m} \boldsymbol{\theta}_{i,m}) - \\
& \left[\frac{w_{i,m}^2}{\lambda_{i,m}} + \frac{1}{2} w_{i,m}^2 + \frac{1}{2} M_{i,m}^2 \right]
\end{aligned} \quad (3-74)$$

根据式(3-23)、式(3-44)和式(3-45)可得

$$\begin{aligned}
\dot{V}_{m-1} \leq & -q_{m-1} \|e\|^2 + \eta_{m-1} + \sum_{i=1}^N \sum_{l=1}^n \frac{1}{2} \tilde{\boldsymbol{\theta}}_{i,l}^T \tilde{\boldsymbol{\theta}}_{i,l} - \\
& \frac{1}{2\lambda_{\max}(\mathbf{H}^{\kappa(t)-1})} \left(\frac{\partial P(\mathbf{x}_1)}{\partial \mathbf{x}_1} \right)^T \mathbf{H}^{\kappa(t)-1} \left(\frac{\partial P(\mathbf{x}_1)}{\partial \mathbf{x}_1} \right) + \\
& \sum_{i=1}^N \left[\sum_{l=1}^{m-1} \frac{\rho_{i,l}}{\sigma_{i,l}} \tilde{\boldsymbol{\theta}}_{i,l}^T \boldsymbol{\theta}_{i,l} - \sum_{l=2}^{m-1} c_{i,l} s_{i,l}^2 + \sum_{l=2}^{m-1} \left(\frac{1}{\lambda_{i,l}} - 1 \right) w_{i,l}^2 + \right. \\
& \left. \frac{1}{2} \sum_{l=2}^{m-1} M_{i,m-1}^2 + \frac{1}{2} (s_{i,m}^2 + w_{i,m}^2) \right]
\end{aligned} \quad (3-75)$$

将式(3-75)代入式(3-74)可得

$$\begin{aligned}
\dot{V}_m \leq & -q_m \|e\|^2 + \eta_m + \sum_{i=1}^N \sum_{l=1}^n \frac{1}{2} \tilde{\boldsymbol{\theta}}_{i,l}^T \tilde{\boldsymbol{\theta}}_{i,l} - \\
& \frac{1}{2\lambda_{\max}(\mathbf{H}^{\kappa(t)-1})} \left(\frac{\partial P(\mathbf{x}_1)}{\partial \mathbf{x}_1} \right)^T \mathbf{H}^{\kappa(t)-1} \left(\frac{\partial P(\mathbf{x}_1)}{\partial \mathbf{x}_1} \right) + \\
& \sum_{i=1}^N \left[\sum_{l=1}^m \frac{\rho_{i,l}}{\sigma_{i,l}} \tilde{\boldsymbol{\theta}}_{i,l}^T \boldsymbol{\theta}_{i,l} - \sum_{l=2}^m c_{i,l} s_{i,l}^2 - \sum_{l=2}^m \left(\frac{1}{\lambda_{i,l}} - 1 \right) w_{i,l}^2 + \right. \\
& \left. \frac{1}{2} \sum_{l=2}^m M_{i,m}^2 + \frac{1}{2} (s_{i,m+1}^2 + w_{i,m+1}^2) \right]
\end{aligned} \quad (3-76)$$

式中

$$q_m = q_{m-1} - \frac{1}{2} \sum_{i=1}^N (k_{i,m}^2 + \gamma_{i,m}^{q2}) \quad (3-77)$$

$$\eta_m = \eta_{m-1} + \frac{1}{2} \sum_{i=1}^N \|\boldsymbol{\epsilon}_{i,m}^q\|^2 \quad (3-78)$$

第 n 步 定义第 n 步误差变量 $s_{i,n} = \hat{x}_{i,n} - v_{i,n}$ 和滤波器误差 $w_{i,n} = v_{i,n} - x_{i,n}^*$ 。对误差变量 $s_{i,n}$ 求导可得

$$\begin{aligned}\dot{s}_{i,n} &= \dot{\hat{x}}_{i,n} - \dot{v}_{i,n} \\ &= u_i + k_{i,n}e_{i,1} + \theta_{i,n}^T \varphi_{i,n} + \tilde{\theta}_{i,n}^T \varphi_{i,n} + \epsilon_{i,n}^q + \Delta g_{i,n}^q - \dot{v}_{i,n}\end{aligned}\quad (3-79)$$

使用滤波器技术可以获得状态变量 $v_{i,n}$ 为

$$\lambda_{i,n} \dot{v}_{i,n} + v_{i,n} = x_{i,n}^*, \quad v_{i,n}(0) = x_{i,n}^*(0) \quad (3-80)$$

进一步,由方程(3-26)可得

$$\dot{w}_{i,n} = \dot{v}_{i,n} - \dot{x}_{i,n}^* = -\frac{w_{i,n}}{\lambda_{i,n}} + B_{i,n} \quad (3-81)$$

式中: $\lambda_{i,n}$ 为设计参数; $B_{i,n} = -\dot{x}_{i,n}^*$, 存在一个正整数 $M_{i,n}$, 使得 $|B_{i,n}| \leq M_{i,n}$ 。

构造 Lyapunov 函数:

$$V_n = V_{n-1} + \sum_{i=1}^N V_{i,n} = V_{n-1} + \frac{1}{2} \sum_{i=1}^N \left\{ s_{i,n}^2 + \frac{1}{\sigma_{i,n}} \tilde{\theta}_{i,n}^T \tilde{\theta}_{i,n} + w_{i,n}^2 \right\} \quad (3-82)$$

式中: $\sigma_{i,n}$ 为设计参数。

对 Lyapunov 函数求导可得

$$\dot{V}_n = \dot{V}_{n-1} + \sum_{i=1}^N \left\{ s_{i,n} \dot{s}_{i,n} + \frac{1}{\sigma_{i,n}} \tilde{\theta}_{i,n}^T \dot{\tilde{\theta}}_{i,n} + w_{i,n} \dot{w}_{i,n} \right\} \quad (3-83)$$

将式(3-79)代入式(3-83)可得

$$\begin{aligned}\dot{V}_n &= \dot{V}_{n-1} + \sum_{i=1}^N \left[s_{i,n} (u_i + k_{i,n}e_{i,1} + \theta_{i,n}^T \varphi_{i,n} + \tilde{\theta}_{i,n}^T \varphi_{i,n} + \epsilon_{i,n}^q + \Delta g_{i,n}^q - \right. \\ &\quad \left. \dot{v}_{i,n}) + \frac{1}{\sigma_{i,n}} \tilde{\theta}_{i,n}^T \dot{\tilde{\theta}}_{i,n} + w_{i,n} \dot{w}_{i,n} \right]\end{aligned}\quad (3-84)$$

根据 Young's 不等式可得

$$s_{i,n} k_{i,n} e_{i,1} \leq \frac{1}{2} s_{i,n}^2 + \frac{1}{2} k_{i,n}^2 \|e_{i,1}\|^2 \quad (3-85)$$

$$s_{i,n} \epsilon_{i,n}^q \leq \frac{1}{2} s_{i,n}^2 + \frac{1}{2} \|\epsilon_{i,n}^q\|^2 \quad (3-86)$$

$$s_{i,n} \Delta g_{i,n}^q \leq \frac{1}{2} s_{i,n}^2 + \frac{1}{2} \gamma_{i,n}^{q2} \|e_{i,n}\|^2 \quad (3-87)$$

根据式(3-85)~式(3-87),式(3-84)可以改写为

$$\begin{aligned}\dot{V}_n &\leq \dot{V}_{n-1} + \sum_{i=1}^N \left[s_{i,n} (u_i + \theta_{i,n}^T \varphi_{i,n} + \tilde{\theta}_{i,n}^T \varphi_{i,n} - \dot{v}_{i,n}) + \frac{3}{2} s_{i,n}^2 + \frac{1}{2} k_{i,n}^2 \|e_{i,1}\|^2 + \right. \\ &\quad \left. \frac{1}{2} \|\epsilon_{i,n}^q\|^2 + \frac{1}{2} \gamma_{i,n}^{q2} \|e_{i,n}\|^2 - \frac{1}{\sigma_{i,n}} \tilde{\theta}_{i,n}^T \dot{\tilde{\theta}}_{i,n} + w_{i,n} \dot{w}_{i,n} \right]\end{aligned}\quad (3-88)$$

设计控制输入 $u_i(t)$ 和第 n 步自适应律 $\theta_{i,n}$

$$u_i = -c_{i,n}s_{i,n} - 2s_{i,n} - \theta_{i,n}^T \varphi_{i,n}(\hat{\mathbf{X}}_{i,n}) + \frac{x_{i,n}^* - v_{i,n}}{\lambda_{i,n}} \quad (3-89)$$

$$\dot{\theta}_{i,n} = \sigma_{i,n} \varphi_{i,n}(\hat{\mathbf{X}}_{i,n}) s_{i,n} - \rho_{i,n} \theta_{i,n} \quad (3-90)$$

式中: $\rho_{i,n}$ 为设计参数。

根据式(3-88), 将式(3-81)、式(3-89)和式(3-90)代入式(3-88)可得

$$\begin{aligned} \dot{V}_n \leq & -q_{n-1} \|\mathbf{e}\|^2 + \eta_{n-1} + \sum_{i=1}^N \sum_{l=1}^n \frac{1}{2} \tilde{\theta}_{i,l}^T \tilde{\theta}_{i,l} - \\ & \frac{1}{2\lambda_{\max}(\mathbf{H}^{\kappa(t)-1})} \left(\frac{\partial P(\mathbf{x}_1)}{\partial \mathbf{x}_1} \right)^T \mathbf{H}^{\kappa(t)-1} \left(\frac{\partial P(\mathbf{x}_1)}{\partial \mathbf{x}_1} \right) + \sum_{i=1}^N \left[\sum_{l=1}^{n-1} \frac{\rho_{i,l}}{\sigma_{i,l}} \tilde{\theta}_{i,l}^T \theta_{i,l} - \right. \\ & \left. \sum_{l=2}^{n-1} c_{i,l} s_{i,l}^2 + \sum_{l=2}^{n-1} \left(\frac{1}{\lambda_{i,l}} - 1 \right) w_{i,l}^2 + \frac{1}{2} \sum_{l=2}^{n-1} M_{i,l}^2 + \frac{1}{2} (s_{i,n}^2 + w_{i,n}^2) \right] + \\ & \sum_{i=1}^N \left[s_{i,n} \left(-c_{i,n} s_{i,n} - 2s_{i,n} - \theta_{i,n}^T \varphi_{i,n}(\hat{\mathbf{X}}_{i,n}) + \frac{x_{i,n}^* - v_{i,n}}{\lambda_{i,n}} + \theta_{i,n}^T \varphi_{i,n} + \right. \right. \\ & \left. \left. \tilde{\theta}_{i,n}^T \varphi_{i,n} - \dot{v}_{i,n} \right) + \frac{3}{2} s_{i,n}^2 + \frac{1}{2} k_{i,n}^2 \|\mathbf{e}_{i,1}\|^2 + \frac{1}{2} \|\epsilon_{i,n}^q\|^2 + \frac{1}{2} \gamma_{i,n}^{q2} \|\mathbf{e}_{i,n}\|^2 - \right. \\ & \left. \frac{1}{\sigma_{i,n}} \tilde{\theta}_{i,n}^T (\sigma_{i,n} \varphi_{i,n}(\hat{\mathbf{X}}_{i,n}) s_{i,n} - \rho_{i,n} \theta_{i,n}) + w_{i,n} \left(-\frac{w_{i,n}}{\lambda_{i,n}} + B_{i,n} \right) \right] \quad (3-91) \end{aligned}$$

根据 Young's 不等式, $w_{i,n} B_{i,n} \leq \frac{1}{2} w_{i,n}^2 + \frac{1}{2} M_{i,n}^2$ 成立, 由此可得

$$\begin{aligned} \dot{V}_n \leq & -q_n \|\mathbf{e}\|^2 + \eta_n + \sum_{i=1}^N \sum_{l=1}^n \frac{1}{2} \tilde{\theta}_{i,l}^T \tilde{\theta}_{i,l} - \frac{1}{2\lambda_{\max}(\mathbf{H}^{\kappa(t)-1})} \left(\frac{\partial P(\mathbf{x}_1)}{\partial \mathbf{x}_1} \right)^T \mathbf{H}^{\kappa(t)-1} \left(\frac{\partial P(\mathbf{x}_1)}{\partial \mathbf{x}_1} \right) + \\ & \sum_{i=1}^N \left[\sum_{l=1}^n \frac{\rho_{i,l}}{\sigma_{i,l}} \tilde{\theta}_{i,l}^T \theta_{i,l} - \sum_{l=2}^n c_{i,l} s_{i,l}^2 - \sum_{l=2}^n \left(\frac{1}{\lambda_{i,l}} - 1 \right) w_{i,l}^2 + \frac{1}{2} \sum_{l=2}^n M_{i,l}^2 \right] \quad (3-92) \end{aligned}$$

式中

$$q_n = q_{n-1} - \frac{1}{2} \sum_{i=1}^N (k_{i,n}^2 + \gamma_{i,n}^{q2}) \quad (3-93)$$

$$\eta_n = \eta_{n-1} + \frac{1}{2} \sum_{i=1}^N \|\epsilon_{i,n}^q\|^2 \quad (3-94)$$

根据 Young's 不等式可得

$$\tilde{\boldsymbol{\theta}}_{*,l}^T \boldsymbol{\theta}_{*,l} \leq -\frac{1}{2} \tilde{\boldsymbol{\theta}}_{*,l}^T \tilde{\boldsymbol{\theta}}_{*,l} + \frac{1}{2} \boldsymbol{\theta}_{*,l}^{*T} \boldsymbol{\theta}_{*,l}^* \quad (3-95)$$

由此可得

$$\begin{aligned} \dot{V}_n &\leq -q_n \|\mathbf{e}\|^2 + \eta_n + \sum_{i=1}^N \sum_{l=1}^n \frac{1}{2} \tilde{\boldsymbol{\theta}}_{i,l}^T \tilde{\boldsymbol{\theta}}_{i,l} - \\ &\quad \frac{1}{2\lambda_{\max}(\mathbf{H}^{\kappa(t)-1})} \left(\frac{\partial P(\mathbf{x}_1)}{\partial \mathbf{x}_1} \right)^T \mathbf{H}^{\kappa(t)-1} \left(\frac{\partial P(\mathbf{x}_1)}{\partial \mathbf{x}_1} \right) + \\ &\quad \sum_{i=1}^N \left[-\sum_{l=1}^n \frac{\rho_{i,l}}{2\sigma_{i,l}} \tilde{\boldsymbol{\theta}}_{i,l}^T \tilde{\boldsymbol{\theta}}_{i,l} + \sum_{l=1}^n \frac{\rho_{i,l}}{2\sigma_{i,l}} \boldsymbol{\theta}_{i,l}^{*T} \boldsymbol{\theta}_{i,l}^* - \right. \\ &\quad \left. \sum_{l=2}^n c_{i,l} s_{i,l}^2 - \sum_{l=2}^n \left(\frac{1}{\lambda_{i,l}} - 1 \right) w_{i,l}^2 + \frac{1}{2} \sum_{l=2}^n M_{i,l}^2 \right] \end{aligned} \quad (3-96)$$

定义变量

$$\zeta = \eta_n + \sum_{i=1}^N \sum_{l=1}^n \frac{\rho_{i,l}}{2\sigma_{i,l}} \boldsymbol{\theta}_{i,l}^{*T} \boldsymbol{\theta}_{i,l}^* + 2u(n-1) \quad (3-97)$$

将式(3-97)代入式(3-96)可得

$$\begin{aligned} \dot{V}_n &\leq -q_n \|\mathbf{e}\|^2 + \sum_{i=1}^N \left[-\sum_{l=2}^n c_{i,l} s_{i,l}^2 - \sum_{l=1}^n \left(\frac{\rho_{i,l}}{2\sigma_{i,l}} - \frac{1}{2} \right) \tilde{\boldsymbol{\theta}}_{i,l}^T \tilde{\boldsymbol{\theta}}_{i,l} - \sum_{l=2}^n \left(\frac{1}{\lambda_{i,l}} - 1 \right) w_{i,l}^2 \right] - \\ &\quad \frac{1}{2\lambda_{\max}(\mathbf{H}^{\kappa(t)-1})} \left(\frac{\partial P(\mathbf{x}_1)}{\partial \mathbf{x}_1} \right)^T \mathbf{H}^{\kappa(t)-1} \left(\frac{\partial P(\mathbf{x}_1)}{\partial \mathbf{x}_1} \right) + \zeta \end{aligned} \quad (3-98)$$

式中: $c_{i,l} > 0 (l=2, 3, \dots, n)$; $\frac{\rho_{i,l}}{2\sigma_{i,l}} - \frac{1}{2} > 0 (l=1, 2, \dots, n)$; $\frac{1}{\lambda_{i,l}} - 1 > 0 (l=2, 3, \dots, n)$;

$$\frac{1}{2\lambda_{\max}(\mathbf{H}^{\kappa(t)-1})} > 0。$$

定义

$$C = \min \left\{ 2 \frac{q_n}{\lambda_{\min}(\mathbf{P})}, \frac{1}{\lambda_{\max}(\mathbf{H}^{\kappa(t)-1})}, 2c_{i,l}, 2 \left(\frac{\rho_{i,l}}{2\sigma_{i,l}} - \frac{1}{2} \right), 2 \left(\frac{1}{\lambda_{i,l}} - 1 \right) \right\} \quad (3-99)$$

进一步,式(3-98)可写为

$$\dot{V}_n \leq -CV_n + \zeta \quad (3-100)$$

根据引理 1.4 可以得出系统式(3-1)中的所有信号在闭环系统中可以保持半全局最终一致有界,并且最终收敛到分布式优化最优解 $\mathbf{x}^*$ 的邻域内。

3.3 仿真实例

仿真实例：首先选取 Duffing-Holmes 混沌系统为例,研究其分布式优化问题。系统表示如下:

$$\begin{cases} \dot{x}_{i,1} = x_{i,2} + g_{i,1}^{\chi_i(t)}(\mathbf{X}_{i,1}) \\ \dot{x}_{i,2} = u_i + g_{i,2}^{\chi_i(t)}(\mathbf{X}_{i,2}) \\ y_i = x_{i,1} \end{cases}, \quad i = 1, 2, 3, 4, 5 \quad (3-101)$$

系统内未知非线性函数为

$$\begin{cases} g_{1,1}^q = g_{2,1}^q = g_{3,1}^q = g_{4,1}^q = g_{5,1}^q = 0 \\ g_{1,2}^1 = x_{1,1} - 0.25x_{1,2} - x_{1,1}^3 + 0.3\cos t \\ g_{1,2}^2 = 2x_{1,1} - 0.25x_{1,2} - x_{1,1}^3 \\ g_{2,2}^1 = x_{2,1} - 0.25x_{2,2} - x_{2,1}^3 + 0.1(x_{2,1}^2 + x_{2,2}^2)^{1/2} + 0.3\cos t \\ g_{2,2}^2 = x_{2,1}^2 \\ g_{3,2}^1 = x_{3,1} - 0.25x_{3,2} - x_{3,1}^3 + 0.2\sin t (x_{3,1}^2 + 2x_{3,2}^2)^{1/2} + 0.3\cos t \\ g_{3,2}^2 = x_{3,1}^2 - x_{3,2}^3 \\ g_{4,2}^1 = x_{4,1}^2 \\ g_{4,2}^2 = x_{4,1} - 0.25x_{4,2} - x_{4,1}^3 + 0.2\sin t (2x_{4,1}^2 + 2x_{4,2}^2)^{1/2} + 0.3\cos t \\ g_{5,2}^1 = x_{5,1}^3 + x_{5,2}^2 \\ g_{5,2}^2 = x_{5,1} - 0.1x_{5,2} - x_{5,1}^3 + 0.2\sin t (x_{5,1}^2 + x_{5,2}^2)^{1/2} + 0.3\cos t \end{cases} \quad (3-102)$$

系统初始状态 $\mathbf{x}_i$ 设置为

$$\begin{aligned} \mathbf{x}_1(0) &= [0.1, 0.1]^T, \quad \mathbf{x}_2(0) = [0.2, 0.2]^T, \quad \mathbf{x}_3(0) = [0.3, 0.3]^T, \\ \mathbf{x}_4(0) &= [0.4, 0.4]^T, \quad \mathbf{x}_5(0) = [0.5, 0.5]^T \end{aligned}$$

观测器参数设置为

$$k_{1,1} = k_{2,1} = k_{3,1} = k_{4,1} = k_{5,1} = 500, \quad k_{1,2} = k_{2,2} = k_{3,2} = k_{4,2} = k_{5,2} = 5000$$

初始状态 $\hat{\mathbf{x}}_i$ 设置为

$$\hat{\mathbf{x}}_1 = [0.2, 0.2]^T, \quad \hat{\mathbf{x}}_2 = [0.3, 0.3]^T, \quad \hat{\mathbf{x}}_3 = [0.4, 0.4]^T,$$

$$\hat{\mathbf{x}}_4 = [0.5, 0.5]^T, \quad \hat{\mathbf{x}}_5 = [0.6, 0.6]^T$$

定义参考信号 $x_d = \sin t$ 。给定局部目标函数如下：

$$\begin{cases} f_1(x_{1,1}) = 3.2x_{1,1}^2 - 6.4x_d x_{1,1} + 3.2x_d^2 + 1 \\ f_2(x_{2,1}) = 4.6x_{2,1}^2 - 9.2x_d x_{2,1} + 4.6x_d^2 + 2 \\ f_3(x_{3,1}) = 2.5x_{3,1}^2 - 5x_d x_{3,1} + 2.5x_d^2 + 3 \\ f_4(x_{4,1}) = 2.8x_{4,1}^2 - 5.6x_d x_{4,1} + 2.8x_d^2 + 4 \\ f_5(x_{5,1}) = 3.5x_{5,1}^2 - 7x_d x_{5,1} + 3.5x_d^2 + 5 \end{cases} \quad (3-103)$$

根据式(3-42)、式(3-43)、式(3-89)和式(3-90)设计虚拟控制律、自适应律和控制输入。选择设计参数为 $c_{i,1}=4, c_{i,2}=3, \sigma_{i,1}=\sigma_{i,2}=1, \rho_{i,1}=\rho_{i,2}=80, \lambda_{i,2}=0.1$ 。

图 3-1~图 3-8 为仿真结果。图 3-1 为多智能体通信拓扑图。图 3-2 和图 3-3 为通过本章所提方法得到的系统状态跟踪图像以及智能体 1 的观测器估计值。图 3-4 为智能体输出

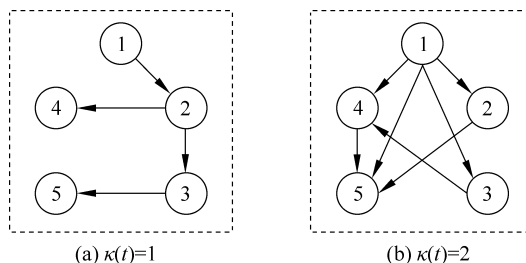


图 3-1 多智能体通信拓扑图

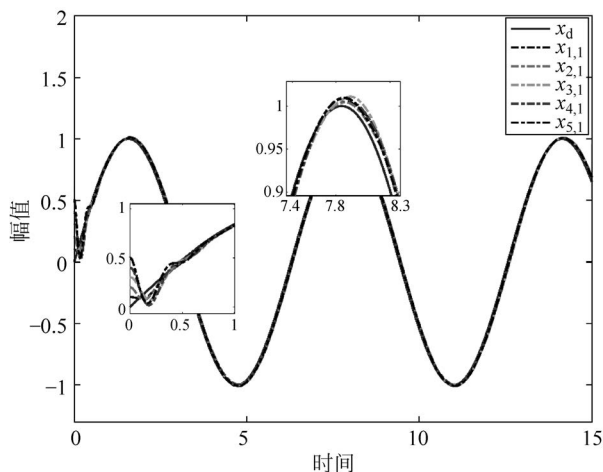


图 3-2 状态 $x_{i,1}$ 以及跟踪信号轨迹 y_d



彩图

信号与参考信号之间的追踪误差,可以看出追踪误差在一个合理的范围内。图 3-5 为本章所提出方法的得到的控制输入轨迹。图 3-6 为本章所构造的惩罚函数的数值轨迹,可以看出惩罚函数最终能够收敛到最小值附近。图 3-7 和图 3-8 给出拓扑切换信号和系统切换信号。

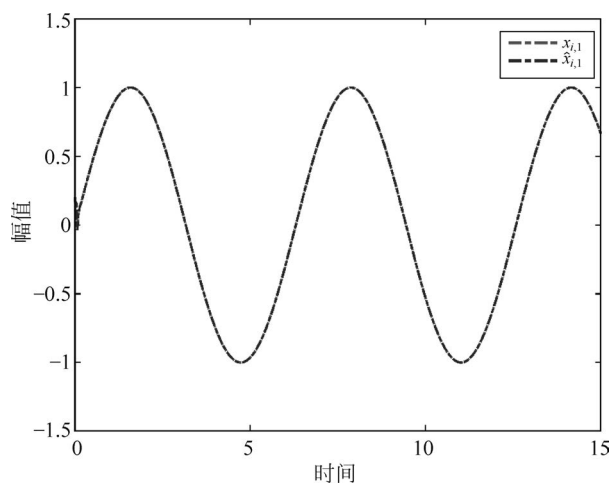


图 3-3 状态 $x_{1,1}$ 以及观测器信号 $\hat{x}_{1,1}$

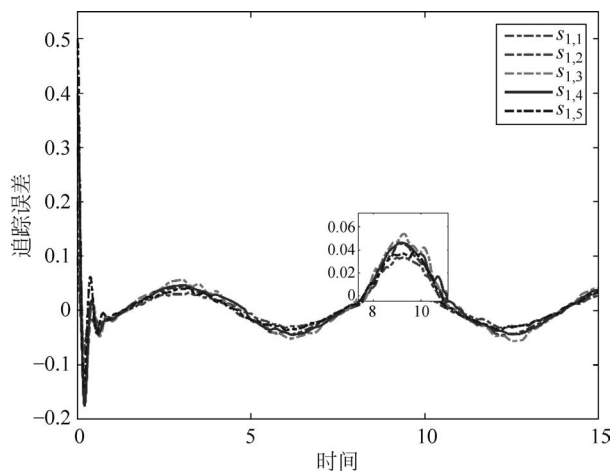


图 3-4 追踪误差 $s_{i,1}$



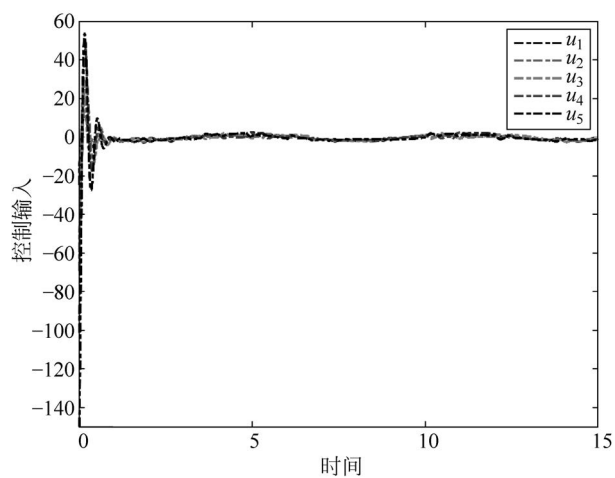
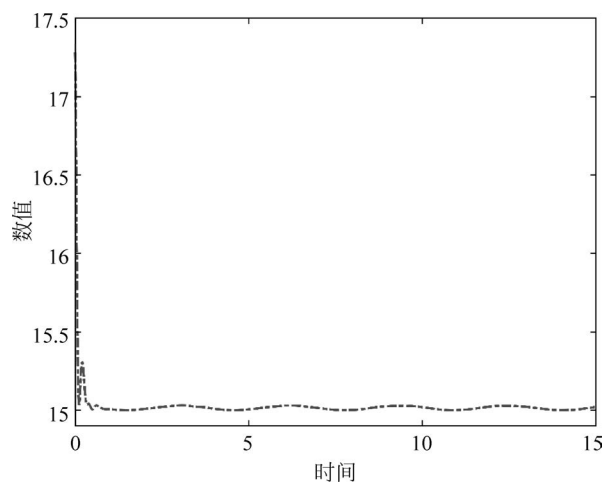
彩图



彩图



彩图

图 3-5 控制输入 u_i 图 3-6 惩罚函数 $P(x_1)$

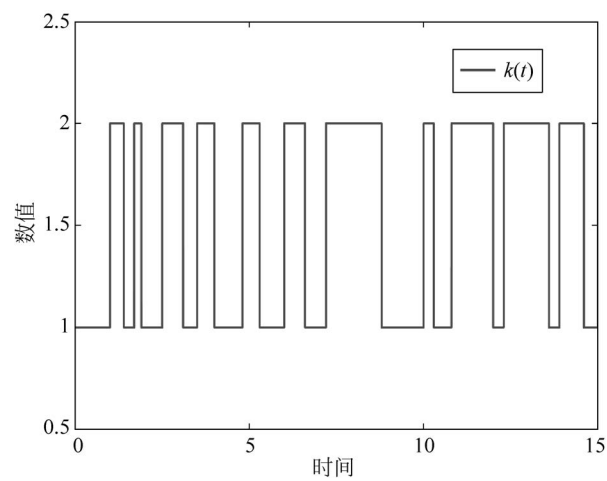


图 3-7 拓扑切换信号

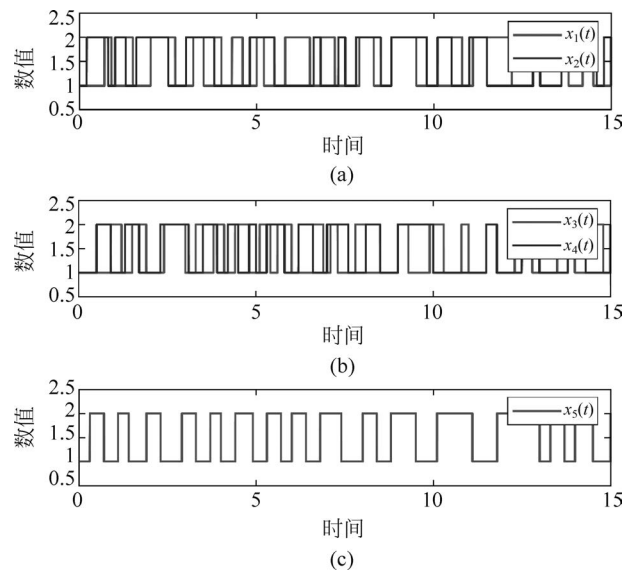


图 3-8 系统切换信号



彩图