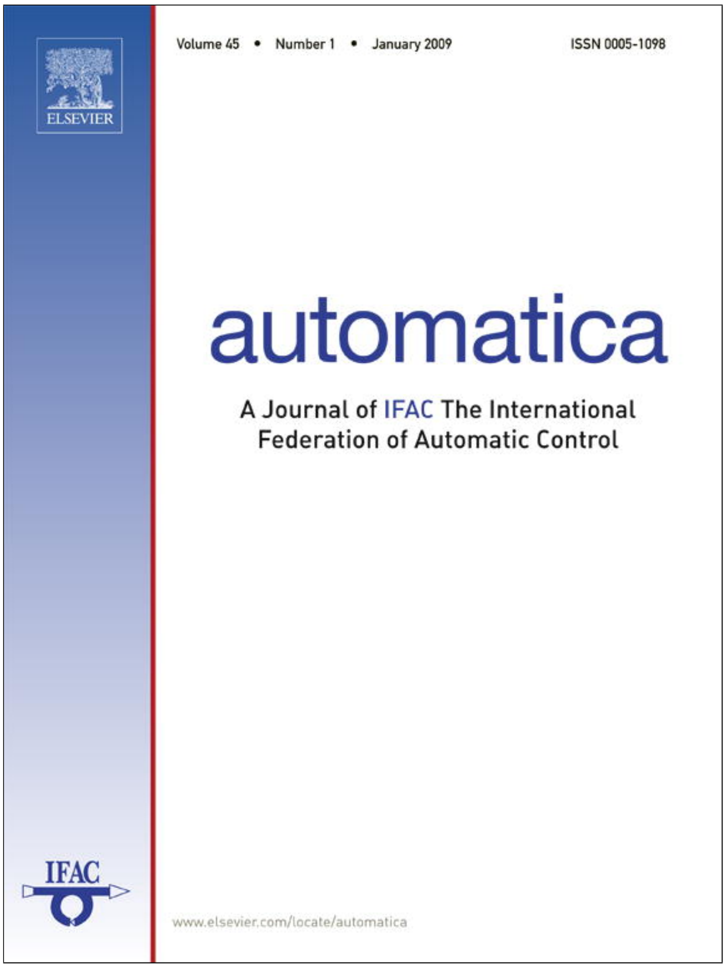
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Decentralized adaptive backstepping stabilization of interconnected systems with dynamic input and output interactions☆

Changyun Wen[a,*], Jing Zhou[b], Wei Wang[a]

[a] School of Electrical and Electronic Engineering, Nanyang Technological University, Nanyang Avenue, Singapore 639798, Singapore

[b] Faculty of Information Technology, Mathematics and Electrical Engineering, Norwegian University of Science and Technology, Trondheim, 7491, Norway

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So far there is still no result available for backstepping based decentralized adaptive stabilization of unknown systems with interactions directly depending on subsystem inputs, even though such interactions commonly exist in practice. In this paper, we provide a solution to this problem by considering both input and output dynamic interactions. To clearly illustrate our approaches, we will start with linear systems and then extend the results to nonlinear systems. Each local controller, designed simply based on the model of each subsystem by using the standard adaptive backstepping technique without any modification, only employs local information to generate control signals. It is shown that the designed decentralized adaptive backstepping controllers can globally stabilize the overall interconnected system asymptotically. The L_2 and L_∞ norms of the system outputs are also established as functions of design parameters. This implies that the transient system performance can be adjusted by choosing suitable design parameters.

1. Introduction

In the control of uncertain complex interconnected systems, decentralized adaptive control technique is an efficient and practical strategy to be employed for many reasons such as ease of design, familiarity and so on. However, simplicity of the design makes the analysis of the overall designed system quite difficult. Thus the obtained results with rigorous analysis are still limited. Based on conventional adaptive approach, several results on global stability and steady state tracking were reported, see for examples Datta and Ioannou (1992), Ioannou (1986), Ortega and Herrera (1993), Wen (1995), Wen and Hill (1992), and Wen and Soh (1999). However, transient performance is not ensured and non-adjustable by changing design parameters due to the methods used.

Since backstepping technique was proposed, it has been widely used to design adaptive controllers for uncertain systems (Krstic, Kanellakopoulos, & Kokotovic, 1995). This technique has a number of advantages over the conventional approaches such as providing a promising way to improve the transient performance of adaptive systems by tuning design parameters. Because of such advantages, research on decentralized adaptive control using backstepping technique has also received great attention. In Wen (1994), the first result on decentralized adaptive control using such a technique was reported without restriction on subsystem relative degrees. More general class of systems with the consideration of unmodeled dynamics was studied in Wen and Soh (1997) and Zhang, Wen, and Soh (2000). In Jiang (2000) and Jain and Khorrami (1997), nonlinear interconnected systems were addressed. In Jiang and Repperger (2001) and Liu and Li (2002), decentralized adaptive stabilization for nonlinear systems with dynamic interactions depending on subsystem outputs or unmodeled dynamics is studied. In Wen and Zhou (2007), systems with non-smooth hysteresis nonlinearities and higher order nonlinear interactions were considered and in Liu, Zhang, and Jiang (2007) results for stochastic nonlinear systems were established. More recently, a result on backstepping adaptive tracking was established in Zhou and Wen (2008). However, except for Jiang and Repperger (2001), Wen and Soh (1997) and Zhang et al. (2000), all the results are only applicable to systems with interaction effects bounded by static functions of subsystem outputs. This is restrictive as it is a kind of matching condition in the sense that the effects of all the unmodeled interactions to a local subsystem must be in the range space of the output of this subsystem. Note that in Wen and Soh (1997) only the local control laws are obtained using the backstepping technique, while local parameter estimators are still designed using the conventional gradient type of approaches. Thus transient performance of the adaptive systems is not established.

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* Corresponding author. Tel.: +65 6790 4947; fax: +65 6792 0415.
E-mail address: ecywen@ntu.edu.sg (C. Wen).

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$$y(t)=\begin{bmatrix} G_1(p)+\nu_{11}H_{11}(p) & \dots & \nu_{1N}H_{1N}(p) \\ \nu_{21}H_{21}(p) & \dots & \nu_{2N}H_{2N}(p) \\ \vdots & \ddots & \vdots \\ \nu_{N1}H_{N1}(p) & \dots & G_N(p)+\nu_{NN}H_{NN}(p) \end{bmatrix} u(t) + \begin{bmatrix} \mu_{11}\Delta_{11}(p) & \dots & \mu_{1N}\Delta_{1N}(p) \\ \mu_{21}\Delta_{21}(p) & \dots & \mu_{2N}\Delta_{2N}(p) \\ \vdots & \ddots & \vdots \\ \mu_{N1}\Delta_{N1}(p) & \dots & \mu_{NN}\Delta_{NN}(p) \end{bmatrix} y(t)$$

Box I.

In Jiang and Repperger (2001) and Zhang et al. (2000), the interactions are not directly depending on subsystem inputs.

In practice, an interconnected system unavoidably has dynamic interactions involving both subsystem inputs and outputs. Especially, dynamic interactions directly depending on subsystem inputs commonly exist. For example, the non-zero off-diagonal elements of a transfer function matrix represent such interactions. So far there is still no result reported to control systems with interactions directly depending on subsystem inputs even for the case of static input interactions by using the backstepping technique. This is due to the challenge of handling the input variables and their derivatives of all subsystems during the recursive design steps. In this paper, we will use the backstepping design approach in Krstic et al. (1995) to design decentralized adaptive controllers for both linear and nonlinear systems having such interactions. It is shown that the designed controllers can globally stabilize the overall interconnected system asymptotically. This reveals that the standard backstepping controller offers an additional advantage to conventional adaptive controllers in term of its robustness against unmodeled dynamics and interactions. For conventional adaptive controllers without any modification, they are non-robust as shown by counter examples in Rohrs, Valavani, Athans, and Stein (1982). Besides global stability, the L_2 and L_∞ norms of the system outputs are also shown to be bounded by functions of design parameters. Thus the transient system performance is tunable by adjusting design parameters. To achieve these results, two key techniques are used in our analysis. Firstly, we transform the dynamic interactions from subsystem inputs to dynamic interactions from subsystem states. Secondly, we introduce two dynamic systems associated with interaction dynamics. In this way, the effects of unmodeled interactions are bounded by static functions of the state variables of subsystems. To clearly illustrate our approach, we will start with linear systems involving block diagram manipulation. Then the obtained results are generalized to nonlinear systems.

2. Modeling of linear interconnected systems

To show our ideas, we first consider linear systems consisting of N interconnected subsystems described in Box I, where $u \in R^N$ and $y \in R^N$ are inputs and outputs respectively, p denotes the differential operator $\frac{d}{dt}$, $G_i(p)$, $H_{ij}(p)$ and $\Delta_{ij}(p)$, $i, j = 1, \dots, N$, are rational functions of p, ν_{ij} and μ_{ij} are positive scalars. With p replaced by s, the corresponding $G_i(s)$, $H_{ij}(s)$ and $\Delta_{ij}(s)$ are the transfer functions of each local subsystem and interactions, respectively.

A block diagram including the ith and jth subsystems is shown in Fig. 1.

Remark 1. $\nu_{ij}H_{ij}(p)u_j(t)$ and $\mu_{ij}\Delta_{ij}(p)y_j(t)$ denote the dynamic interactions from the input and output of the jth subsystem to the ith subsystem for $j \neq i$, or unmodeled dynamics of the ith subsystem for $j = i$ with ν_{ij} and μ_{ij} indicating the strength of the interactions or unmodeled dynamics. Such interactions are rather general. However there is no result on decentralized backstepping adaptive control applicable to interactions directly from the inputs when using the backstepping technique.

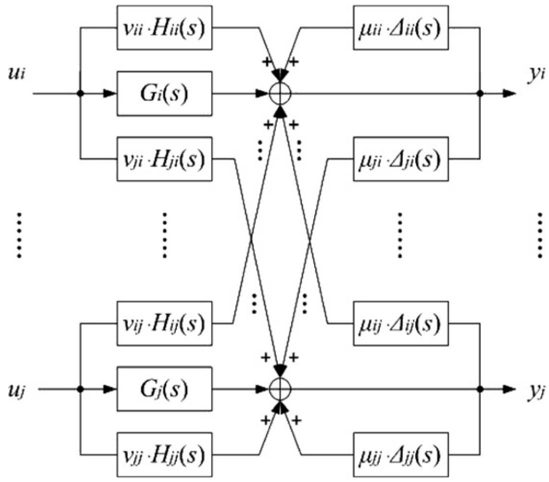

Fig. 1. Block diagram including the ith and jth subsystems.

For the system, we have the following assumptions.

Assumption 2.1. For each subsystem,

$$G_i(s) = \frac{B_i(s)}{A_i(s)} = \frac{b_{i,m_i}s^{m_i} + \dots + b_{i,1}s + b_{i,0}}{s^{n_i} + a_{i,(n_i-1)}s^{n_i-1} + \dots + a_{i,1}s + a_{i,0}} \quad (1)$$

where $a_{i,j}, j = 0, \dots, n_i - 1$ and $b_{i,k}, k = 0, \dots, m_i$ are unknown constants, $B_i(s)$ is a Hurwitz polynomial. The order n_i, the sign of b_{i,m_i} and the relative degree ρ_i $(=n_i - m_i)$ are known;

Assumption 2.2. For all $i, j = 1, \dots, N$, $\Delta_{ij}(s)$ is stable, strictly proper and has a unity high frequency gain, and $H_{ij}(s)$ is stable with a unity high frequency gain and its relative degree is larger than ρ_j.

The block diagram in Fig. 1 can be transformed to Fig. 2. Clearly, the ith subsystem has the following state space realization:

$$\dot{x}_i = A_i x_i - a_i x_{i,1} + \begin{bmatrix} 0 \\ b_i \end{bmatrix} u_i \quad (2)$$

$$y_i = x_{i,1} + \sum_{j=1}^{N} \nu_{ij}\frac{H_{ij}(p)}{G_j(p)}x_{j,1} + \sum_{j=1}^{N}\mu_{ij}\Delta_{ij}(p)y_j, \quad (3)$$

where

$$A_i = \begin{bmatrix} 0_{n_i-1} & I_{n_i-1} \\ 0 & 0^T_{n_i-1} \end{bmatrix}$$

$$a_i = [a_{i,(n_i-1)}, \dots, a_{i,0}]^T, \qquad b_i = [b_{i,m_i}, \dots, b_{i,0}]^T \quad (4)$$

where $0_{n_i-1} \in R^{(n_i-1)}$. In the design of a local controller for the ith subsystem, we only consider transfer function $G_i(s)$, i.e,

$$\dot{x}_i = A_i x_i - a_i x_{i,1} + \begin{bmatrix} 0 \\ b_i \end{bmatrix} u_i \quad (5)$$

$$y_i = x_{i,1}, \quad \text{for } i = 1, \dots, N. \quad (6)$$

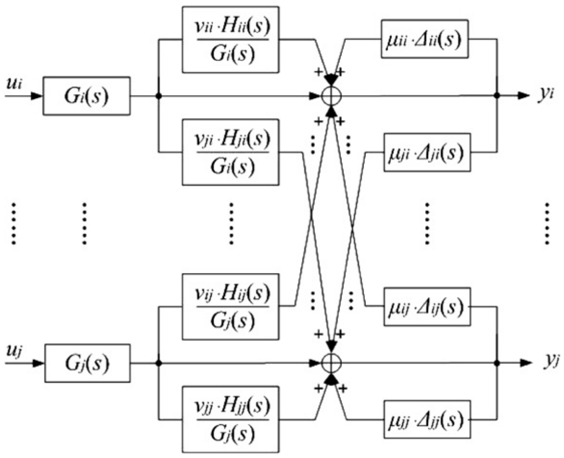

Fig. 2. Transformed block diagram of Fig. 1.

But in analysis, we will also take into account the effects of the unmodeled interactions and subsystem unmodeled dynamics, i.e.

$$\sum_{j=1}^{N} \nu_{ij} \frac{H_{ij}(p)}{G_j(p)} x_{j,1} + \sum_{j=1}^{N} \mu_{ij} \Delta_{ij}(p) y_j. \tag{7}$$

Remark 2. It is clear that the effect of the dynamic interactions or unmodeled dynamics given in (7) cannot be bounded by functions of the outputs y_j, $j = 1, 2, \ldots, N$, as assumed in the previous work. Instead, based on the given assumptions, it satisfies,

$$\left| \sum_{j=1}^{N} \nu_{ij} \frac{H_{ij}(p)}{G_j(p)} x_{j,1} + \sum_{j=1}^{N} \mu_{ij} \Delta_{ij}(p) y_j \right| \le c_{0,i} + \sum_{j=1}^{N} c_{1,ij} \sup_{0 \le \tau \le t} |x_{j,1}(\tau)| + \sum_{j=1}^{N} c_{2,ij} \sup_{0 \le \tau \le t} |y_j(\tau)|$$

for $i = 1, \ldots, N$ (8)

for some constants $c_{0,i}$, $c_{1,ij}$, and $c_{2,ij}$. The above bound involves infinite memory of state $x_{j,1}$ depending on inputs u_j and outputs y_j, which makes the analysis of decentralized backstepping adaptive control systems difficult. This is the main reason why there is still no result available for such a class of systems, due to the requirement of changing coordinates and handling the input variables and their derivatives during the recursive design steps.

Note that in our analysis given in Section 3, bound (8) will not be used. Instead, we will consider signals generated from two dynamic systems related to interactions or unmodeled dynamics to bound the effect.

Our problem is formulated to design decentralized controllers only using local signals to ensure the stability of the overall interconnected system and regulate all the subsystem outputs to zeros. The system transient performance should also be adjustable by changing design parameters in certain sense.

3. Decentralized adaptive control of linear systems

3.1. Decentralized state estimation filters

We only present the decentralized adaptive controllers designed using the standard backstepping technique in Krstic et al. (1995), without giving the details. Firstly, a local filter using only local input and output is designed to estimate the states of each unknown local system as follows:

$$\dot{\lambda}_i = A_{i,0} \lambda_i + e_{n_i,n_i} u_i \tag{9}$$

$$\dot{\eta}_i = A_{i,0} \eta_i + e_{n_i,n_i} y_i \tag{10}$$

$$\upsilon_{i,k} = (A_{i,0})^k \lambda_i, \quad k = 0, \ldots, m_i \tag{11}$$

$$\xi_{i,n_i} = -(A_{i,0})^{n_i} \eta_i \tag{12}$$

where $A_{i,0} = A_i - k_i (e_{n_i,1})^{\mathrm{T}}$, the vector $k_i = [k_{i,1}, \ldots, k_{i,n_i}]^{\mathrm{T}}$ is chosen so that the matrix $A_{i,0}$ is Hurwitz, and $e_{i,k}$ denotes the kth coordinate vector in R^i. Hence there exists a P_i such that $P_i A_{i,0} + A_{i,0} P_i^{\mathrm{T}} = -I_{n_i}$, $P_i = P_i^{\mathrm{T}} > 0$. With these designed filters our state estimate is given by

$$\hat{x}_i = \xi_{i,n_i} + \Omega_i^{\mathrm{T}} \theta_i \tag{13}$$

where

$$\theta_i^{\mathrm{T}} = [b_i^{\mathrm{T}}, a_i^{\mathrm{T}}] \tag{14}$$

$$\Omega_i^{\mathrm{T}} = [\upsilon_{i,m_i}, \ldots, \upsilon_{i,1}, \upsilon_{i,0}, \Xi_i] \tag{15}$$

$$\Xi_i = -[(A_{i,0})^{n_i - 1} \eta_i, \ldots, A_{i,0} \eta_i, \eta_i]. \tag{16}$$

Note that

$$\begin{aligned} \dot{\xi}_{i,n_i} &= -(A_{i,0})^{n_i} \left(A_{i,0} \eta_i + e_{n_i,n_i} y_i \right) \\ &= A_{i,0} \xi_{i,n_i} + k_i y_i \end{aligned} \tag{17}$$

$$\begin{aligned} \dot{\Xi}_i &= -[(A_{i,0})^{n_i-1} \dot{\eta}_i, \ldots, A_{i,0} \dot{\eta}_i, \dot{\eta}_i] \\ &= -[(A_{i,0})^{n_i-1}, \ldots, A_{i,0}, I_{n_i}](A_{i,0} \eta_i + e_{n_i,n_i} y_i) \\ &= A_{i,0} \Xi_i - I_{n_i} y_i \end{aligned} \tag{18}$$

$$\dot{\upsilon}_{i,k} = A_{i,0} \upsilon_{i,k} + e_{n_i,n_i-k} u_i, \quad k = 0, \ldots, m_i. \tag{19}$$

Then from (13), the derivative of $\hat{x}_i$ is given as

$$\begin{aligned} \dot{\hat{x}}_i &= \dot{\xi}_{i,n_i} + \dot{\Omega}_i^{\mathrm{T}} \theta_i \\ &= A_{i,0} \xi_{i,n_i} + k_i y_i + A_{i,0} [\upsilon_{i,m_i}, \ldots, \upsilon_{i,1}, \upsilon_{i,0}, \Xi_i] \theta_i \\ &\quad - I_{n_i} y_i a_i + [0, b_i^{\mathrm{T}}]^{\mathrm{T}} u_i \\ &= A_{i,0} \hat{x}_i - (a_i - k_i) y_i + [0, b_i^{\mathrm{T}}]^{\mathrm{T}} u_i. \end{aligned} \tag{20}$$

From (2) and (20) the state estimation error $\epsilon_i = x_i - \hat{x}_i$ satisfies

$$\dot{\epsilon}_i = A_{i,0} \epsilon_i + (a_i - k_i) \left(\sum_{j=1}^{N} \nu_{ij} \frac{H_{ij}(s)}{G_j(s)} x_{j,1} + \sum_{j=1}^{N} \mu_{ij} \Delta_{ij}(s) y_j \right). \tag{21}$$

Now we replace (2) with a new system, whose states depend on those of filters (9)–(12) and thus are available for control design, as follows:

$$\begin{aligned} \dot{y}_i &= b_{i,m_i} \upsilon_{i,(m_i,2)} + \xi_{i,(n_i,2)} + \bar{\delta}_i^{\mathrm{T}} \theta_i + \epsilon_{i,2} \\ &\quad + (s + a_{i,(n_i-1)}) \left(\sum_{j=1}^{N} \nu_{ij} \frac{H_{ij}(s)}{G_j(s)} x_{j,1} + \sum_{j=1}^{N} \mu_{ij} \Delta_{ij}(s) y_j \right) \end{aligned} \tag{22}$$

$$\dot{\upsilon}_{i,(m_i,q)} = \upsilon_{i,(m_i,q+1)} - k_{i,q} \upsilon_{i,(m_i,1)} \quad q = 2, \ldots, \rho_i - 1 \tag{23}$$

$$\dot{\upsilon}_{i,(m_i,\rho_i)} = \upsilon_{i,(m_i,\rho_i+1)} - k_{i,\rho_i} \upsilon_{i,(m_i,1)} + u_i \tag{24}$$

where

$$\delta_i^{\mathrm{T}} = [\upsilon_{i,(m_i,2)}, \upsilon_{i,(m_i-1,2)}, \ldots, \upsilon_{i,(0,2)}, \Xi_{i,2} - y_i (e_{n_i,1})^{\mathrm{T}}] \tag{25}$$

$$\bar{\delta}_i^{\mathrm{T}} = [0, \upsilon_{i,(m_i-1,2)}, \ldots, \upsilon_{i,(0,2)}, \Xi_{i,2} - y_i (e_{n_i,1})^{\mathrm{T}}] \tag{26}$$

and $\upsilon_{i,(m_i,2)}$, $\epsilon_{i,2}$, $\xi_{i,(n_i,2)}$, $\Xi_{i,2}$ denote the second entries of υ_{i,m_i}, ϵ_i, ξ_{i,n_i}, Ξ_i respectively.

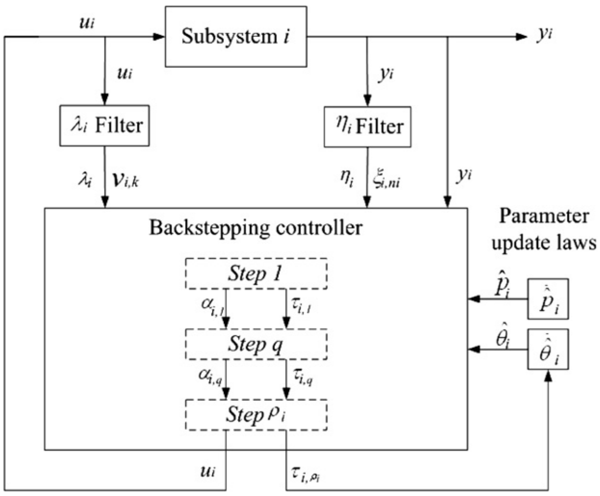

Fig. 3. Control block diagram.

Remark 3. The output signals λ_i, η_i, $v_{i,k}$, ξ_{i,n_i} of filters (9)–(12) are available for feedback. They are also used to generate an estimate $\hat{x}_i$ of system states x_i in (13), with an estimation error given by (21). The error will converge to zero in the absence of interactions and unmodeled dynamics. However, the estimate $\hat{x}_i$ is not used in the controller design because it involves unknown parameter vector θ_i which is unavailable. But the state estimation error in (21) will be considered in system analysis, as it may not converge to zero unconditionally due to its dependence on interactions and unmodeled dynamics in our case. A block diagram is given in Fig. 3 to show the signal flow of the filters to the controller of the ith subsystem.

3.2. Design of decentralized adaptive controllers

As usual in backstepping approach (Krstic et al., 1995), the following change of coordinates is made.

$$z_{i,1} = y_i \tag{27}$$

$$z_{i,q} = v_{i,(m_i,q)} - \alpha_{i,(q-1)}, \quad q = 2, 3, \ldots, \rho_i. \tag{28}$$

To illustrate the controller design procedures, we now give a brief description on the first step.

Step 1: From (22), (27) and (28), we have

$$\dot{z}_{i,1} = b_{i,m_i}(z_{i,2} + \alpha_{i,1}) + \xi_{i,(n_i,2)} + \bar{\delta}_i^{\mathrm{T}}\theta_i + \epsilon_{i,2} + (s + a_{i,(n_i-1)})\left(\sum_{j=1}^{N} v_{ij}\frac{H_{ij}(s)}{G_j(s)}x_{j,1} + \sum_{j=1}^{N}\mu_{ij}\Delta_{ij}(s)y_j\right). \tag{29}$$

The virtual control law $\alpha_{i,1}$ is designed as

$$\alpha_{i,1} = \hat{p}_i\bar{\alpha}_{i,1} \tag{30}$$

$$\bar{\alpha}_{i,1} = -c_{i1}z_{i,1} - l_{i1}z_{i,1} - \xi_{i,(n_i,2)} - \bar{\delta}_i^{\mathrm{T}}\hat{\theta}_i \tag{31}$$

where c_{i1}, l_{i1} are positive constants, $\hat{p}_i$ is an estimate of $p_i = 1/b_{i,m_i}$ and $\hat{\theta}_i$ is an estimate of θ_i. Note that

$$b_{i,m_i}\alpha_{i,1} = b_{i,m_i}\hat{p}_i\bar{\alpha}_{i,1} = \bar{\alpha}_{i,1} - b_{i,m_i}\tilde{p}_i\bar{\alpha}_{i,1} \tag{32}$$

$$\begin{aligned}\bar{\delta}_i^{\mathrm{T}}\tilde{\theta}_i + b_{i,m_i}z_{i,2} &= \bar{\delta}_i^{\mathrm{T}}\tilde{\theta}_i + \tilde{b}_{i,m_i}z_{i,2} + \hat{b}_{i,m_i}z_{i,2}\\ &= (\delta_i^{\mathrm{T}} - \hat{p}_i\bar{\alpha}_{i,1}e_{(n_i+m_i+1),1})^{\mathrm{T}}\tilde{\theta}_i + \hat{b}_{i,m_i}z_{i,2}\end{aligned} \tag{33}$$

where $\hat{b}_{i,m_i}$ is an estimate of b_{i,m_i}, $\tilde{b}_{i,m_i} = b_{i,m_i} - \hat{b}_{i,m_i}$, $\tilde{p}_i = p_i - \hat{p}_i$ and $\tilde{\theta}_i = \theta_i - \hat{\theta}_i$. Then we have

$$\begin{aligned}\dot{z}_{i,1} = {}& -c_{i1}z_{i,1} - l_{i1}z_{i,1} - b_{i,m_i}\tilde{p}_i\bar{\alpha}_{i,1} + \hat{b}_{i,m_i}z_{i,2} + \epsilon_{i,2}\\ &+ (\delta_i - \hat{p}_i\bar{\alpha}_{i,1}e_{(n_i+m_i+1),1})^{\mathrm{T}}\tilde{\theta}_i + (s + a_{i,(n_i-1)})\\ &\times\left(\sum_{j=1}^{N} v_{ij}\frac{H_{ij}(s)}{G_j(s)}x_{j,1} + \sum_{j=1}^{N}\mu_{ij}\Delta_{ij}(s)y_j\right).\end{aligned} \tag{34}$$

We now define a function V_{i1} as

$$V_{i1} = \frac{1}{2}(z_{i,1})^2 + \frac{1}{l_{i1}}\epsilon_i^{\mathrm{T}}P_i\epsilon_i + \frac{1}{2}\tilde{\theta}_i^{\mathrm{T}}\Gamma_i^{-1}\tilde{\theta}_i + \frac{|b_{i,m_i}|}{2\gamma_i'}\tilde{p}_i^2 \tag{35}$$

where Γ_i is a positive definite design matrix and γ_i' is a positive design parameter. Then

$$\begin{aligned}\dot{V}_{i1} = {}& -c_{i,1}(z_{i,1})^2 - \frac{l_{i1}}{2}(z_{i,1})^2 + \hat{b}_{i,m_i}z_{i,1}z_{i,2}\\ &- |b_{i,m_i}|\tilde{p}_i\frac{1}{\gamma_i'}[\gamma_i'\mathrm{sgn}(b_{i,m_i})\bar{\alpha}_{i,1}z_{i,1} + \dot{\hat{p}}_i]\\ &+ \tilde{\theta}_i^{\mathrm{T}}\Gamma_i^{-1}[\Gamma_i(\delta_i - \hat{p}_i\bar{\alpha}_{i,1}e_{(n_i+m_i+1),1})z_{i,1} - \dot{\hat{\theta}}_i] - \frac{l_{i1}}{2}(z_{i,1})^2\\ &+ \epsilon_{i,2}z_{i,1} - \frac{1}{l_{i1}}\|\epsilon_i\|^2 + z_{i,1}(s + a_{i,(n_i-1)})\\ &\times\left(\sum_{j=1}^{N} v_{ij}\frac{H_{ij}(s)}{G_j(s)}x_{j,1} + \sum_{j=1}^{N}\mu_{ij}\Delta_{ij}(s)z_{j,1}\right) - \frac{2}{l_{i1}}(a_i - k_i)^{\mathrm{T}}P_i\epsilon_i\\ &\times\left(\sum_{j=1}^{N} v_{ij}\frac{H_{ij}(s)}{G_j(s)}x_{j,1} + \sum_{j=1}^{N}\mu_{ij}\Delta_{ij}(s)z_{j,1}\right).\end{aligned} \tag{36}$$

To handle the unknown indefinite $\tilde{p}_i$, $\tilde{\theta}_i$-terms in (36), we choose the update law of $\hat{p}$ and a tuning function $\tau_{i,1}$ as

$$\dot{\hat{p}}_i = -\gamma_i'\mathrm{sgn}(b_{i,m_i})\bar{\alpha}_{i,1}z_{i,1} \tag{37}$$

$$\tau_{i,1} = (\delta_i - \hat{p}_i\bar{\alpha}_{i,1}e_{(n_i+m_i+1),1})z_{i,1}. \tag{38}$$

It follows that

$$\begin{aligned}\dot{V}_{i1} \le {}& -c_{i,1}(z_{i,1})^2 - \frac{l_{i1}}{2}(z_{i,1})^2 - \frac{1}{2l_{i1}}\|\epsilon_i\|^2 + \hat{b}_{i,m_i}z_{i,1}z_{i,2}\\ &+ \tilde{\theta}_i^{\mathrm{T}}\Gamma_i^{-1}[\Gamma_i\tau_{i,1} - \dot{\hat{\theta}}_i] + z_{i,1}(s + a_{i,(n_i-1)})\\ &\times\left(\sum_{j=1}^{N} v_{ij}\frac{H_{ij}(s)}{G_j(s)}x_{j,1} + \sum_{j=1}^{N}\mu_{ij}\Delta_{ij}(s)z_{j,1}\right) - \frac{2}{l_{i1}}(a_i - k_i)^{\mathrm{T}}P_i\epsilon_i\\ &\times\left(\sum_{j=1}^{N} v_{ij}\frac{H_{ij}(s)}{G_j(s)}x_{j,1} + \sum_{j=1}^{N}\mu_{ij}\Delta_{ij}(s)z_{j,1}\right).\end{aligned} \tag{39}$$

After going through design steps q for $q = 2, \ldots, \rho_i$ as in Krstic et al. (1995), we have the ith local controller

$$u_i = \alpha_{i,\rho_i} - v_{i,(m_i,\rho_i+1)} \tag{40}$$

where $\alpha_{i,1}$ is designed in (30) and

$$\begin{aligned}\alpha_{i,2} = {}& -\hat{b}_{i,m_i}z_{i,1} - \left[c_{i2} + l_{i2}\left(\frac{\partial\alpha_{i,1}}{\partial y_i}\right)^2\right]z_{i,2} + \bar{B}_{i,2}\\ &+ \frac{\partial\alpha_{i,1}}{\partial\hat{p}_i}\dot{\hat{p}}_i + \frac{\partial\alpha_{i,1}}{\partial\hat{\theta}_i}\Gamma_i\tau_{i,2}\end{aligned} \tag{41}$$

$$\begin{aligned}\alpha_{i,q} = {}& -z_{i,(q-1)} - \left[c_{iq} + l_{iq}\left(\frac{\partial\alpha_{i,(q-1)}}{\partial y_i}\right)^2\right]z_{i,q} + \bar{B}_{i,q}\\ &+ \frac{\partial\alpha_{i,(q-1)}}{\partial\hat{p}_i}\dot{\hat{p}}_i + \frac{\partial\alpha_{i,(q-1)}}{\partial\hat{\theta}_i}\Gamma_i\tau_{i,q}\\ &- \left(\sum_{k=2}^{q-1} z_{i,k}\frac{\partial\alpha_{i,(k-1)}}{\partial\hat{\theta}_i}\right)\Gamma_i\frac{\partial\alpha_{i,(q-1)}}{\partial y_i}\delta_i\\ & q = 3, \ldots, \rho_i\end{aligned} \tag{42}$$

$$\bar{B}_{i,q} = \frac{\partial \alpha_{i,(q-1)}}{\partial y_i}(\xi_{i,(n_i,2)} + \delta_i^T \hat{\theta}_i) + \frac{\partial \alpha_{i,(q-1)}}{\partial \eta_i}(A_{i,0}\eta_i + e_{n_i,n_i}y_i) + k_{i,q}v_{i,(m_i,1)} + \sum_{j=1}^{m_i+q-1} \frac{\partial \alpha_{i,(q-1)}}{\partial \lambda_{i,j}}(-k_{i,j}\lambda_{i,1} + \lambda_{i,(j+1)})$$

$$q = 2, \ldots, \rho_i,\ i = 1, \ldots, N \tag{43}$$

where Γ_i is a positive definite matrix and $c_{iq}, l_{iq}, \gamma_i'$ are positive constants. With $\tau_{i,1}$ in (38), other tuning functions $\tau_{i,q}$ for $q = 2, \ldots, \rho_i$ are given as

$$\tau_{i,q} = \tau_{i,(q-1)} - \frac{\partial \alpha_{i,(q-1)}}{\partial y_i}\delta_i z_{i,q}. \tag{44}$$

Then parameter update law $\hat{\theta}_i$ is designed to be

$$\dot{\hat{\theta}}_i = \Gamma_i \tau_{i,\rho_i}. \tag{45}$$

The designed controller for the ith subsystem only uses the local signals, as shown in its block diagram Fig. 3.

3.3. Stability analysis

We define $z_i(t) = [z_{i,1}, z_{i,2}, \ldots, z_{i,\rho_i}]^{\mathrm{T}}$. The ith subsystem (2) and (3) subject to local controller (40) is characterized by

$$\dot{z}_i = A_{zi}z_i + W_{\epsilon i}\epsilon_{i,2} + W_{\theta i}^{\mathrm{T}}\tilde{\theta}_i - b_{i,m_i}\bar{\alpha}_{i,1}\tilde{p}_i e_{\rho_i,1} + W_{\epsilon i}\left[(s + a_{i,(n_i-1)})\left(\sum_{j=1}^{N} \nu_{ij}\frac{H_{ij}(s)}{G_j(s)}x_{j,1} + \sum_{j=1}^{N}\mu_{ij}\Delta_{ij}(s)y_j\frac{H_{ij}(s)}{G_j(s)}\right)\right] \tag{46}$$

where A_{zi} is a matrix having the similar structure to the scalar systems given in Krstic et al. (1995) (see box II),

$$W_{\epsilon i} = \left[1, -\frac{\partial \alpha_{i,1}}{\partial y_i}, \ldots, -\frac{\partial \alpha_{i,(\rho_i-1)}}{\partial y_i}\right], \tag{47}$$

$$W_{\theta i}^{\mathrm{T}} = W_{\epsilon i}\delta_i^{\mathrm{T}} - \hat{p}_i\bar{\alpha}_{i,1}e_{\rho_i,1}e_{\rho_i,1}{}^{\mathrm{T}}, \tag{48}$$

where the terms $\sigma_{i,(k,q)}$ are due to the terms $\frac{\partial \alpha_{i,(k-1)}}{\partial \hat{\theta}_i}\Gamma_i(\tau_{i,q} - \tau_{i,(q-1)})$ in the $z_{i,q}$ equation.

With respect to (46), we consider a function V_{ρ_i} defined as:

$$V_{\rho_i} = \sum_{q=1}^{\rho_i}\left(\frac{1}{2}(z_{i,q})^2 + \frac{1}{l_{iq}}\epsilon_i{}^{\mathrm{T}}P_i\epsilon_i\right) + \frac{1}{2}\tilde{\theta}_i^{\mathrm{T}}\Gamma_i^{-1}\tilde{\theta}_i + \frac{|b_{i,m_i}|}{2\gamma_i'}\tilde{p}_i^2. \tag{49}$$

From (21) and (22) and the designed controllers (40)–(45), it can be shown that the derivative of V_{ρ_i} satisfies

$$\begin{aligned}
\dot{V}_{\rho_i} &= \sum_{q=1}^{\rho_i} z_{i,q}\dot{z}_{i,q} - \tilde{\theta}_i^{\mathrm{T}}\Gamma^{-1}\dot{\hat{\theta}}_i - \frac{|b_{i,m_i}|}{\gamma_i'}\tilde{p}_i\dot{\hat{p}}_i \\
&\quad - \sum_{q=1}^{\rho_i}\frac{1}{l_{iq}}\|\epsilon_i\|^2 - 2\sum_{q=1}^{\rho_i}\frac{1}{l_{iq}}(a_i - k_i)^{\mathrm{T}}P_i\epsilon_i \\
&\quad \times \left(\sum_{j=1}^{N}\nu_{ij}\frac{H_{ij}(s)}{G_j(s)}x_{j,1} + \sum_{j=1}^{N}\mu_{ij}\Delta_{ij}(s)y_j\right) \\
&\le -\sum_{q=1}^{\rho_i} c_{iq}(z_{i,q})^2 - \sum_{q=2}^{\rho_i}\frac{l_{iq}}{2}\left(\frac{\partial \alpha_{i,(q-1)}}{\partial y_i}\right)^2(z_{i,q})^2 \\
&\quad - \sum_{q=1}^{\rho_i}\frac{1}{2l_{iq}}\|\epsilon_i\|^2 - \sum_{q=2}^{\rho_i} z_{i,q}\frac{\partial \alpha_{i,(q-1)}}{\partial y_i}\epsilon_{i,2} \\
&\quad - \frac{l_{i1}}{2}(z_{i,1})^2 + z_{i,1}(s + a_{i,(n_i-1)})\left(\sum_{j=1}^{N}\nu_{ij}\frac{H_{ij}(s)}{G_j(s)}x_{j,1} + \sum_{j=1}^{N}\mu_{ij}\Delta_{ij}(s)z_{j,1}\right) - \sum_{q=2}^{\rho_i}\left[\frac{l_{iq}}{2}\left(\frac{\partial \alpha_{i,(q-1)}}{\partial y_i}\right)^2(z_{i,q})^2\right. \\
&\quad + z_{i,q}\frac{\partial \alpha_{i,(q-1)}}{\partial y_i}(s + a_{i,(n_i-1)})\left(\sum_{j=1}^{N}\nu_{ij}\frac{H_{ij}(s)}{G_j(s)}x_{j,1} + \left.\sum_{j=1}^{N}\mu_{ij}\Delta_{ij}(s)z_{j,1}\right)\right] - \sum_{q=1}^{\rho_i}\left[\frac{1}{2l_{iq}}\|\epsilon_i\|^2\right. \\
&\quad \left. + \Phi_i^{\mathrm{T}}\epsilon_i\left(\sum_{j=1}^{N}\nu_{ij}\frac{H_{ij}(s)}{G_j(s)}x_{j,1} + \sum_{j=1}^{N}\mu_{ij}\Delta_{ij}(s)z_{j,1}\right)\right] \\
&\le -\sum_{q=1}^{\rho_i} c_{iq}(z_{i,q})^2 + \sum_{q=1}^{\rho_i}\frac{1}{l_{iq}}(s + a_{i,(n_i-1)})^2 L_i \\
&\quad - \sum_{q=1}^{\rho_i}\frac{1}{4l_{iq}}\|\epsilon_i\|^2 + \sum_{q=1}^{\rho_i} 2\|\Phi_i\|^2 l_{iq}L_i
\end{aligned} \tag{50}$$

where

$$\Phi_i^{\mathrm{T}} = \frac{2}{l_{iq}}(a_i - k_i)^{\mathrm{T}}P_i \tag{51}$$

$$Ł_i = \left(\sum_{j=1}^{N}\nu_{ij}\frac{H_{ij}(s)}{G_j(s)}x_{j,1}\right)^2 + \left(\sum_{j=1}^{N}\mu_{ij}\Delta_{ij}(s)z_{j,1}\right)^2. \tag{52}$$

To deal with the dynamic interaction or unmodeled dynamics, we show that their effects can be bounded by static functions of system states, as given in Lemma 1 later. Let $h_{i,j}$ and $g_{i,j}$ be the state vectors of systems with transfer functions $H_{ij}(s)G_j^{-1}(s)$ and $\Delta_{ij}(s)$, respectively. They are given by

$$\dot{h}_{i,j} = B_{hi,j}h_{i,j} + b_{hi,j}x_{j,1}$$

$$H_{ij}(s)G_j^{-1}(s)x_{j,1} = (1, 0, \ldots, 0)h_{i,j} \tag{53}$$

$$\dot{g}_{i,j} = A_{gi,j}g_{i,j} + b_{gi,j}y_j$$

$$\Delta_{ij}(s)y_j = (1, 0, \ldots, 0)g_{i,j} \tag{54}$$

where $A_{gi,j}$ and $B_{hi,j}$ are Hurwitz because $\Delta_{ij}(s)$, $H_{ij}(s)$ and $B_j^{-1}(s)$ are stable from Assumptions 2.1 and 2.2. It is obvious that

$$\left\|\Delta_{ij}(s)y_j\right\|^2 \le \|\chi\|^2 \tag{55}$$

$$\left\|\sum_{j=1}^{N} H_{ij}(s)G_j^{-1}(s)x_{j,1}\right\|^2 \le k_{i0}\|\chi\|^2 \tag{56}$$

where $\chi = [\chi_1^{\mathrm{T}}, \ldots, \chi_N^{\mathrm{T}}]^{\mathrm{T}}$ and $\chi_i = [z_i^{\mathrm{T}}, \epsilon_i^{\mathrm{T}}, \tilde{\eta}_i^{\mathrm{T}}, \zeta_i^{\mathrm{T}}, h_{i,1}{}^{\mathrm{T}}, \ldots, h_{i,N}{}^{\mathrm{T}}, g_{i,1}{}^{\mathrm{T}}, \ldots, g_{i,N}{}^{\mathrm{T}}]^{\mathrm{T}}$.

We also have

$$\begin{aligned}
\left\|(s + a_{i,(n_i-1)})\sum_{j=1}^{N} H_{ij}(s)G_j^{-1}(s)x_{j,1}\right\|^2 &= \left\|\sum_{j=1}^{N}(1, 0, \ldots, 0)\dot{h}_{i,j} + a_{i,(n_i-1)}\sum_{j=1}^{N} H_{ij}(s)G_j^{-1}(s)x_{j,1}\right\|^2 \\
&= \left\|\left(\sum_{j=1}^{N}(1, 0, \ldots, 0)[B_{hi,j}h_{i,j} + b_{hi,j}x_{j,1}] + a_{i,(n_i-1)}\right)\sum_{j=1}^{N} H_{ij}(s)G_j^{-1}(s)x_{j,1}\right\|^2
\end{aligned}$$

$$\leq k_{i1}\sum_{j=1}^{N}\|x_{j,1}\|^2 + k_{i2}\|\chi\|^2 \left\|(s+a_{i,(n_i-1)})\sum_{j=1}^{N}\Delta_{ij}(s)y_j\right\|^2 \quad (57)$$

$$= \left\|\sum_{j=1}^{N}(1,0,\ldots,0)[A_{gi,j}g_{i,j}+b_{gi,j}y_j] + a_{i,(n_i-1)}\sum_{j=1}^{N}\Delta_{ij}(s)y_j\right\|^2 \leq k_{i3}\|\chi\|^2 \quad (58)$$

where k_{i0}, k_{i1}, k_{i2} and k_{i3} are constants. It is clear from (3) and (27) that

$$x_{i,1} = z_{i,1} - \sum_{j=1}^{N}\nu_{ij}\frac{H_{ij}(s)}{G_j(s)}x_{j,1} - \sum_{j=1}^{N}\mu_{ij}\Delta_{ij}(s)y_j. \quad (59)$$

Thus

$$\left\|(s+a_{i,(n_i-1)})\sum_{j=1}^{N}H_{ij}(s)G_j^{-1}(s)x_{j,1}\right\|^2 \leq \left[k_{i4} + 2\left(\max_{1\leq,i,j\leq N}\{\nu_{ij}^2\} + \max_{1\leq,i,j\leq N}\{\mu_{ij}^2\}\right)k_{i4}\right]\|\chi\|^2 \quad (60)$$

where $k_{i4} = \max\{k_{i2}+2k_{i1}, 2k_{i1}, 2k_{i1}k_{i0}\}$ are constants and independent of μ_{ij} and ν_{ij}.

Then we can get the following lemma.

Lemma 1. *The effects of the interactions and unmodeled dynamics are bounded as follows*

$$\left\|\sum_{j=1}^{N}\Delta_{ij}(s)z_{j,1}\right\|^2 \leq \|\chi\|^2 \quad (61)$$

$$\left\|\sum_{j=1}^{N}H_{ij}(s)G_j^{-1}(s)x_{j,1}\right\|^2 \leq k_{i0}\|\chi\|^2 \quad (62)$$

$$\left\|(s+a_{i,(n_i-1)})\sum_{j=1}^{N}\Delta_{ij}(s)z_{j,1}\right\|^2 \leq k_{i3}\|\chi\|^2 \quad (63)$$

$$\left\|(s+a_{i,(n_i-1)})\sum_{j=1}^{N}H_{ij}(s)G_j^{-1}(s)x_{j,1}\right\|^2 \leq \left[k_{i4} + 2\left(\max_{1\leq,i,j\leq N}\{\nu_{ij}^2\} + \max_{1\leq,i,j\leq N}\{\mu_{ij}^2\}\right)k_{i4}\right]\|\chi\|^2. \quad (64)$$

With these preliminaries established, we can obtain our first main result stated in the following theorem.

Theorem 1. *Consider the closed-loop adaptive system consisting of the plant in Box I under Assumptions 2.1 and 2.2, the controller (40), the estimators (37), (45), and the filters (9)–(12). There exists a constant μ^* such that for all $\nu_{ij} < \mu^*$ and $\mu_{ij} < \mu^*, i, j = 1, 2, \ldots, N$, all the signals in the system are globally uniformly bounded and $\lim_{t\to\infty} y_i(t) = 0$.*

Proof. To show the stability of the overall system, the state variables of the filters in (10) and state vector ζ_i associated with the zero dynamics of ith subsystems should be considered. Under a similar transformation as in Wen (1994), these variables can be shown to satisfy

$$\dot{\zeta}_i = A_{i,b_i}\zeta_i + \bar{b}_i x_{i,1} \quad (65)$$

$$\dot{\tilde{\eta}}_i = A_{i,0}\tilde{\eta}_i + e_{n_i,n_i}z_{i,1} \quad (66)$$

$$\dot{\eta}_i^r = A_{i,0}\eta_i^r, \qquad \tilde{\eta}_i = \eta_i - \eta_i^r \quad (67)$$

where the eigenvalues of the $m_i \times m_i$ matrix A_{i,b_i} are the zeros of the Hurwitz polynomial $N_i(s)$, $\bar{b}_i \in R^{m_i}$.

A Lyapunov function for the ith local system is defined as

$$V_i = V_{\rho_i} + \frac{1}{l_{\eta i}}\tilde{\eta}_i^T P_i\tilde{\eta}_i + \frac{1}{l_{\zeta i}}\zeta_i^T P_{i,b_i}\zeta_i + \sum_{j=1}^{N}l_{hij}h_{i,j}^T P_{hi,j}h_{i,j} + \sum_{j=1}^{N}l_{gij}g_{i,j}^T P_{gi,j}g_{i,j} \quad (68)$$

where $l_{\eta i}, l_{\zeta i}, l_{hij}, l_{gij}$ are positive constants, and P_{i,b_i}, $P_{hi,j}$ and $P_{gi,j}$ satisfy

$$P_{i,b_i}A_{i,b_i} + A_{i,b_i}^T P_{i,b_i} = -I_{m_i} \quad (69)$$

$$P_{hi,j}B_{hi,j} + B_{hi,j}^T P_{hi,j} = -I_{h_{ij}} \quad (70)$$

$$P_{gi,j}A_{gi,j} + A_{gi,j}^T P_{gi,j} = -I_{g_{ij}}. \quad (71)$$

From Eqs. (3), (50)–(54), (65)–(67) and (69)–(71), we get

$$\begin{aligned}
\dot{V}_i =\ & \dot{V}_{\rho_i} - \frac{1}{l_{\eta i}}\|\tilde{\eta}_i\|^2 + \frac{2}{l_{\eta i}}P_i\tilde{\eta}_i^T e_{n_i,n_i}z_{i,1} - \frac{1}{l_{\zeta i}}\|\zeta_i\|^2 \\
& + \frac{2}{l_{\zeta i}}\zeta_i^T P_{i,b_i}\bar{b}_i x_{i,1} - \sum_{j=1}^{N}l_{hij}\|h_{i,j}\|^2 + 2\sum_{j=1}^{N}l_{hij}h_{i,j}^T P_{hi,j}b_{hi,j}x_{j,1} \\
& - \sum_{j=1}^{N}l_{gij}\|g_{i,j}\|^2 + 2\sum_{j=1}^{N}l_{gij}g_{i,j}^T P_{gi,j}b_{gi,j}z_{j,1} \\
\leq\ & -\frac{1}{2}c_{i1}(z_{i,1})^2 - \sum_{q=2}^{\rho_i}c_{iq}(z_{i,q})^2 - \sum_{q=1}^{\rho_i}\frac{1}{4l_{iq}}\|\epsilon_i\|^2 \\
& - \frac{1}{2l_{\eta i}}\|\tilde{\eta}_i\|^2 - \frac{1}{2l_{\zeta i}}\|\zeta_i\|^2 - \sum_{j=1}^{N}\frac{1}{2}l_{hij}\|h_{i,j}\|^2 \\
& - \sum_{j=1}^{N}\frac{1}{2}l_{gij}\|g_{i,j}\|^2 + \sum_{q=1}^{\rho_i}\frac{1}{l_{iq}}(s+a_{i,(n_i-1)})^2 L_i \\
& + \sum_{q=1}^{\rho_i}2\|\Phi_i\|^2\frac{1}{l_{iq}}L_i - \frac{1}{4l_{\zeta i}}\|\zeta_i\|^2 - \frac{2}{l_{\zeta i}}\zeta_i^T P_{i,b_i}\bar{b}_i \\
& \times\left(\sum_{j=1}^{N}\nu_{ij}\frac{H_{ij}(s)}{G_j(s)}x_{j,1} + \sum_{j=1}^{N}\mu_{ij}\Delta_{ij}(s)z_{j,1}\right) \\
& - \sum_{j=1}^{N}\left[\frac{l_{hij}}{4}\|h_{i,j}\|^2 + 2l_{hij}h_{i,j}^T P_{hi,j}b_{hi,j}\right. \\
& \left.\times\left(\sum_{j=1}^{N}\nu_{ij}\frac{H_{ij}(s)}{G_j(s)}x_{j,1} + \sum_{j=1}^{N}\mu_{ij}\Delta_{ij}(s)z_{j,1}\right)\right] \\
& - \frac{1}{8}c_{i1}(z_{i,1})^2 - \sum_{j=1}^{N}\frac{1}{2}l_{gij}\|g_{i,j}\|^2 + 2\sum_{j=1}^{N}l_{gij}g_{i,j}^T P_{gi,j}b_{gi,j}z_{j,1} \\
& - \frac{1}{8}c_{i1}(z_{i,1})^2 - \sum_{j=1}^{N}\frac{l_{hij}}{4}\|h_{i,j}\|^2 + 2\sum_{j=1}^{N}l_{hij}h_{i,j}^T P_{hi,j}b_{hi,j}z_{j,1} \\
& - \frac{1}{8}c_{i1}(z_{i,1})^2 - \frac{1}{2l_{\eta i}}\|\tilde{\eta}_i\|^2 + \frac{2}{l_{\eta i}}P_i\tilde{\eta}_i^T e_{n_i,n_i}z_{i,1} \\
& - \frac{1}{8}c_{i1}(z_{i,1})^2 - \frac{1}{4l_{\zeta i}}\|\zeta_i\|^2 + \frac{2}{l_{\zeta i}}\zeta_i^T P_{i,b_i}\bar{b}_i z_{i,1}.
\end{aligned} \quad (72)$$

Taking

$$l_{\eta i} \geq \frac{16\|P_i e_{n_i,n_i}\|^2}{c_{i1}}, \qquad l_{\zeta i} \geq \frac{32\|P_{i,b_i}\bar{b}_i\|^2}{c_{i1}} \quad (73)$$

$$l_{hij} \le \frac{c_{j1}}{32N\|P_{hi,j}b_{hi,j}\|^2} \tag{74}$$

$$l_{gij} \le \frac{c_{j1}}{16N\|P_{gi,j}b_{gi,j}\|^2} \tag{75}$$

we then obtain

$$\begin{aligned}
\dot{V}_i \le & -\beta_i\|\chi_i\|^2 + \left[\sum_{q=1}^{\rho_i} 2\|\Phi_i\|^2 l_{iq} + \frac{8}{l_{\zeta i}}\|P_{i,b_i}\bar{b}_i\|^2 \right.\\
& \left. + 8\sum_{j=1}^{N} l_{hij}\|P_{hi,j}b_{hi,j}\|^2\right] L_i + \sum_{j=1}^{N}\frac{1}{4N}c_{j1}(z_{j,1})^2 \\
& + \sum_{q=1}^{\rho_i}\frac{1}{l_{iq}}(s+a_{i,(n_i-1)})^2 L_i - \frac{1}{2}c_{i1}(z_{i,1})^2 \\
\le & -\beta_i\|\chi_i\|^2 - \frac{1}{4}c_{i1}(z_{i,1})^2 + \mu^2\left[k_{i6}\left(\left\|\sum_{j=1}^{N}\frac{H_{ij}(s)}{G_j(s)}x_{j,1}\right\|^2\right.\right.\\
& \left. + \left\|\sum_{j=1}^{N}\Delta_{ij}(s)z_{j,1}\right\|^2\right) + k_{i5}\left(\left\|(s+a_{i,(n_i-1)})\sum_{j=1}^{N}\frac{H_{ij}(s)}{G_j(s)}x_{j,1}\right\|^2\right.\\
& \left.\left. + \left\|(s+a_{i,(n_i-1)})\sum_{j=1}^{N}\Delta_{ij}(s)z_{j,1}\right\|^2\right)\right] \\
& - \left(\frac{1}{4}c_{i1}(z_{i,1})^2 - \sum_{j=1}^{N}\frac{1}{4N}c_{j1}(z_{j,1})^2\right)
\end{aligned} \tag{76}$$

where

$$\begin{aligned}
\beta_i = & \min\left\{\frac{c_{i1}}{4}, c_{i2}, \ldots, c_{i\rho_i}, \sum_{q=1}^{\rho_i}\frac{1}{4l_{iq}}, \frac{1}{2l_{\eta i}}, \frac{1}{2l_{\zeta i}},\right.\\
& \left.\min_{1\le j\le N}\left\{\frac{1}{2}l_{hij}, \frac{1}{2}l_{gij}\right\}\right\}
\end{aligned} \tag{77}$$

$$k_{i5} = \sum_{q=1}^{\rho_i}\frac{1}{l_{iq}} \tag{78}$$

$$k_{i6} = \sum_{q=2}^{\rho_i} 2\|\Phi_i\|^2 l_{iq} + \frac{8}{l_{\zeta i}}\|P_{i,b_i}\bar{b}_i\|^2 + 8\sum_{j=1}^{N} l_{hij}\|P_{hi,j}b_{hi,j}\|^2 \tag{79}$$

$$\mu = \max_{1\le i,j\le N}\{\mu_{ij}, \nu_{ij}\}. \tag{80}$$

Now we define a Lyapunov function for the overall decentralized adaptive control system as

$$V = \sum_{i=1}^{N} V_i. \tag{81}$$

Using Lemma 1 and (76), we have

$$\begin{aligned}
\dot{V} \le & -\sum_{i=1}^{N}\left[\beta - ((1+k_{i0})k_{i6} + (k_{i3}+k_{i4})k_{i5})\,\mu^2\right.\\
& \left. - k_{i4}k_{i5}\mu^4\right]\|\chi\|^2 - \frac{1}{4}\sum_{i=1}^{N} c_{i1}(z_{i,1})^2
\end{aligned} \tag{82}$$

where

$$\beta = \frac{\min_{1\le i\le N}\beta_i}{N}. \tag{83}$$

By taking μ^* in Box III, we have $\dot{V} \le -\frac{1}{4}\sum_{i=1}^{N} c_{i1}(z_{i,1})^2$. This concludes the proof of Theorem 1 that all the signals in the system are globally uniformly bounded. By applying the LaSalle–Yoshizawa theorem, it further follows that $\lim_{t\to\infty} y_i(t) = 0$ for arbitrary initial $x_i(0)$. △

We now derive bounds for system output $y_i(t)$ on both L_2 and L_∞ norms. Firstly, the following definitions are made.

$$d_i^0 = \sum_{q=1}^{\rho_i}\frac{1}{2l_{iq}}. \tag{84}$$

As shown in (82), the derivative of V is given by

$$\dot{V} \le -\sum_{i=1}^{N}\frac{1}{4}c_{i1}(z_{i,1})^2. \tag{85}$$

Since V is non-increasing, we have

$$\begin{aligned}
\|y_i(t)\|_2^2 = & \int_0^\infty \|z_{i,1}(t)\|^2 dt \\
\le & \frac{4}{c_{i1}}(V(0) - V(\infty)) \le \frac{4}{c_{i1}}(V(0))
\end{aligned} \tag{86}$$

$$\|y_i(t)\|_\infty \le \sqrt{2V(0)}. \tag{87}$$

From (67), we can set $\tilde{\eta}_i(0) = 0$ by selecting $\eta_i^r(0) = \eta_i(0)$. Consider the zero initial values

$$\tilde{\eta}_i(0) = 0, \quad \zeta_i(0) = 0, \quad h_{i,j}(0) = 0, \quad g_{i,j}(0) = 0. \tag{88}$$

Note that the initial values $z_{i,q}(0)$ depend on $c_{i1}, \gamma_i', \Gamma_i$. We can set $z_{i,q}(0), q = 2, \ldots, \rho_i$ to zero by suitably initializing our designed filters (9)–(12) as follows:

$$\begin{aligned}
\upsilon_{i,(m_i,q)}(0) = & \alpha_{i,(q-1)}\Big(y_i(0), \hat{\theta}_i(0), \hat{p}_i(0), \eta_i(0),\\
& \lambda_i(0), \upsilon_{i,(m_i,q-1)}(0)\Big), \quad q = 1, \ldots, \rho_i.
\end{aligned} \tag{89}$$

By setting $\tilde{\eta}_i(0) = 0$, $\zeta_i(0) = 0$, $h_{i,j}(0) = 0$, $g_{i,j}(0) = 0$ and $z_{i,q}(0) = 0, q = 2, \ldots, \rho_i$, we have

$$\begin{aligned}
V(0) = & \sum_{i=1}^{N}\frac{1}{2}(y_i(0))^2 + d_i^0\|\epsilon_i(0)\|_{P_i}^2 \\
& + \|\tilde{\theta}_i(0)\|_{\Gamma_i^{-1}}^2 + \frac{|b_{i,m_i}|}{\gamma_i'}|\tilde{p}_i(0)|^2
\end{aligned} \tag{90}$$

where $\|\epsilon_i\|_{P_i}^2 = \epsilon_i^{\mathrm{T}}(0)P_i\epsilon_i(0)$, $\|\tilde{\theta}_i(0)\|_{\Gamma_i^{-1}}^2 = \tilde{\theta}_i^{\mathrm{T}}(0)\Gamma_i^{-1}\tilde{\theta}_i(0)$. Thus the bounds for $y_i(t)$ is established and formally stated in the following theorem.

Theorem 2. *Consider the initial values $z_{i,q}(0) = 0, q = 2, \ldots, \rho_i$, $\tilde{\eta}_i(0) = 0$, $\zeta_i(0) = 0$, $h_{i,j}(0) = 0$ and $g_{i,j}(0) = 0$, the L_2 and L_∞ norms of output $y_i(t)$ are given by*

$$\begin{aligned}
\|y_i(t)\|_2 \le & \frac{2}{\sqrt{c_{i1}}}\left[\sum_{i=1}^{N}\frac{1}{2}(y_i(0))^2 + d_i^0\|\epsilon_i(0)\|_{P_i}^2\right.\\
& \left. + \|\tilde{\theta}_i(0)\|_{\Gamma_i^{-1}}^2 + \frac{|b_{i,m_i}|}{\gamma_i'}|\tilde{p}_i(0)|^2\right]^{1/2}
\end{aligned} \tag{91}$$

$$\begin{aligned}
\|y_i(t)\|_\infty \le & \sqrt{2}\left[\sum_{i=1}^{N}\frac{1}{2}(y_i(0))^2 + d_i^0\|\epsilon_i(0)\|_{P_i}^2\right.\\
& \left. + \|\tilde{\theta}_i(0)\|_{\Gamma_i^{-1}}^2 + \frac{|b_{i,m_i}|}{\gamma_i'}|\tilde{p}_i(0)|^2\right]^{1/2}.
\end{aligned} \tag{92}$$

Remark 4. Regarding the above bound, the following conclusions can be drawn by noting that $\tilde{\theta}_i(0)$, $\tilde{p}_i(0)$, $\epsilon_i(0)$ and $y_i(0)$ are independent of c_{i1}, Γ_i, γ_i'.

- The L_2 norm of output $y_i(t)$ given in (91) depends on the initial estimation errors $\tilde{\theta}_i(0)$, $\tilde{p}_i(0)$ and $\epsilon_i(0)$. The closer the initial estimates to the true values, the better the transient tracking error performance. This bound can also be systematically reduced down to a lower bound by increasing Γ_i, γ_i' and c_{i1}.
- The L_∞ norm of output $y_i(t)$ given in (92) depends on the initial estimation errors $\tilde{\theta}_i(0)$, $\tilde{p}_i(0)$ and $\epsilon_i(0)$ and design parameters Γ_i, γ_i'.

4. Decentralized adaptive control of nonlinear systems

In this section, we extend our approach to control a class of nonlinear interconnected systems.

4.1. Modeling of nonlinear interconnected systems

On the basis of state space realization (2)–(3) for the ith linear subsystem and the modeling of interaction and unmodeled dynamics in (53) and (54), the class of nonlinear systems is described as

$$\dot{x}_i = A_i x_i + \Phi_i(y_i)a_i + \begin{bmatrix} 0 \\ b_i \end{bmatrix}\sigma_i(y_i)u_i \tag{93}$$

$$y_i = x_{i,1} + \sum_{j=1}^{N}\nu_{ij}\mathrm{e}_1^{\mathrm{T}}h_{i,j}(x_{j,1}) + \sum_{j=1}^{N}\mu_{ij}\mathrm{e}_1^{\mathrm{T}}g_{i,j}(y_j) \quad \text{for } i = 1,\ldots,N \tag{94}$$

where A_i, a_i and b_i are defined in (4), $x_i \in R^{n_i}$, $u_i \in R$ and $y_i \in R$ are states, inputs and outputs respectively, $\Phi_i(y_i) \in R^{n_i\times r_i}$ are matrices of nonlinear functions, $\sigma_i(y_i) \in R$ is a nonlinear function, ν_{ij} and μ_{ij} are positive scalars specifying the magnitudes of dynamic interactions and unmodeled dynamics, $h_{i,j}$ and $g_{i,j}$ are dynamic interactions or unmodeled dynamics, which are generated by

$$\dot{h}_{i,j} = f_{hi,j}(h_{i,j}, x_{j,1}) \tag{95}$$

$$\dot{g}_{i,j} = f_{gi,j}(g_{i,j}, y_j). \tag{96}$$

For such a class of systems, we need the following assumptions.

Assumption 4.1. For each subsystem, $a_{i,j}, j = 0,\ldots,n_i-1$ and $b_{i,k}$, $k = 0,\ldots,m_i$ are unknown constants. The polynomial $B_i(s) = b_{i,m_i}s^{m_i}+\cdots+b_{i,1}s+b_{i,0}$ is Hurwitz. The sign of b_{i,m_i} and the relative degree $\rho_i(= n_i - m_i)$ are known and $\sigma_i(y_i) \neq 0, \forall y_i \in R$;

Assumption 4.2. Functions $f_{hi,j}(h_{i,j}, x_{j,1})$ and $f_{gi,j}(g_{i,j}, y_j)$ are continuously differentiable nonlinear functions and globally Lipschitz in $x_{j,1}$ and y_j respectively. Also the following inequalities hold:

$$\|f_{hi,j}(h_{i,j}, x_{j,1})\|^2 \le \varrho_{hij}\|h_{i,j}\|^2 + \bar{\varrho}_{hij}\|x_{j,1}\|^2 \tag{97}$$

$$\|f_{gi,j}(g_{i,j}, y_j)\|^2 \le \varrho_{gij}\|g_{i,j}\|^2 + \bar{\varrho}_{gij}\|y_j\|^2 \tag{98}$$

where ϱ_{hij}, $\bar{\varrho}_{hij}$, ϱ_{gij} and $\bar{\varrho}_{gij}$ are unknown positive constants;

Assumption 4.3. There exist two smooth positive definite radially unbounded functions $V_{hi,j}$ and $V_{gi,j}$ such that the following inequations are satisfied:

$$\frac{\partial V_{hi,j}}{\partial h_{i,j}}f_{hi,j}(h_{i,j}, 0) \le -d_{hij,1}\|h_{i,j}\|^2 \tag{99}$$

$$\left\|\frac{\partial V_{hi,j}}{\partial h_{i,j}}\right\| \le d_{hij,2}\|h_{i,j}\| \tag{100}$$

$$\frac{\partial V_{gi,j}}{\partial g_{i,j}}f_{gi,j}(g_{i,j}, 0) \le -d_{gij,1}\|g_{i,j}\|^2 \tag{101}$$

$$\left\|\frac{\partial V_{gi,j}}{\partial g_{i,j}}\right\| \le d_{gij,2}\|g_{i,j}\| \tag{102}$$

where $d_{hij,1}$, $d_{hij,2}$, $d_{gij,1}$ and $d_{gij,2}$ are positive constants.

4.2. Design of local filters

A local filter using only local input and output is designed as follows:

$$\dot{\lambda}_i = A_{i,0}\lambda_i + e_{n_i,n_i}\sigma_i(y_i)u_i \tag{103}$$

$$\dot{\Xi}_i = A_{i,0}\Xi_i + \Phi_i(y_i) \tag{104}$$

$$\upsilon_{i,k} = (A_{i,0})^k\lambda_i, \quad k = 0,\ldots,m_i \tag{105}$$

$$\dot{\xi}_{i,0} = A_{i,0}\xi_{i,0} + k_i y_i \tag{106}$$

where $A_{i,0}$, $e_{i,k}$ and k_i are defined in the same way as filters (9)–(12). With these designed filters our state estimate is given by

$$\hat{x}_i = \xi_{i,0} + \Omega_i^{\mathrm{T}}\theta_i \tag{107}$$

where

$$\theta_i^{\mathrm{T}} = [b_i^{\mathrm{T}}, a_i^{\mathrm{T}}] \tag{108}$$

$$\Omega_i^{\mathrm{T}} = [\upsilon_{i,m_i},\ldots,\upsilon_{i,1},\upsilon_{i,0},\Xi_i]. \tag{109}$$

The state estimation $\epsilon_i = x_i - \hat{x}_i$ satisfies

$$\dot{\epsilon}_i = A_{i,0}\epsilon_i - k_i\left(\sum_{j=1}^{N}\nu_{ij}\mathrm{e}_1^{\mathrm{T}}h_{i,j}(x_{j,1}) + \sum_{j=1}^{N}\mu_{ij}\mathrm{e}_1^{\mathrm{T}}g_{i,j}(y_j)\right). \tag{110}$$

Thus, system (93) can be expressed in the following form

$$\dot{y}_i = b_{i,m_i}\upsilon_{i,(m_i,2)} + \xi_{i,(0,2)} + \bar{\delta}_i^{\mathrm{T}}\theta_i + \epsilon_{i,2} + \sum_{j=1}^{N}\nu_{ij}\mathrm{e}_1^{\mathrm{T}}f_{hi,j}(h_{i,j}, x_{j,1}) + \sum_{j=1}^{N}\mu_{ij}\mathrm{e}_1^{\mathrm{T}}f_{gi,j}(g_{i,j}, y_j) \tag{111}$$

$$\dot{\upsilon}_{i,(m_i,q)} = \upsilon_{i,(m_i,q+1)} - k_{i,q}\upsilon_{i,(m_i,1)} \tag{112}$$

$$\dot{\upsilon}_{i,(m_i,\rho_i)} = \upsilon_{i,(m_i,\rho_i+1)} - k_{i,\rho_i}\upsilon_{i,(m_i,1)} + \sigma_i(y_i)u_i \tag{113}$$

where

$$\delta_i^{\mathrm{T}} = [\upsilon_{i,(m_i,2)},\ldots,\upsilon_{i,(0,2)},\Xi_{i,2} + e_{n_i,1}^{\mathrm{T}}\Phi_i(y_i)] \tag{114}$$

$$\bar{\delta}_i^{\mathrm{T}} = [0,\upsilon_{i,(m_i-1,2)},\ldots,\upsilon_{i,(0,2)},\Xi_{i,2} + e_{n_i,1}^{\mathrm{T}}\Phi_i(y_i)] \tag{115}$$

and $\upsilon_{i,(m_i,2)}$, $\epsilon_{i,2}$, $\xi_{i,(0,2)}$, $\Xi_{i,2}$ denote the second entries of υ_{i,m_i}, ϵ_i, $\xi_{i,0}$, Ξ_i respectively. All states of the local filters in (103)–(106) are available for feedback.

4.3. Design of decentralized adaptive controllers

Performing similar backstepping procedures to linear systems, we can obtain local adaptive controllers summarized in (116)–(127) below.

Coordinate transformation:

$$z_{i,1} = y_i \tag{116}$$

$$z_{i,q} = \upsilon_{i,(m_i,q)} - \alpha_{i,(q-1)}, \quad q = 2,3,\ldots,\rho_i \tag{117}$$

Control laws:

$$u_i = \frac{1}{\sigma_i(y_i)}\left(\alpha_{i,\rho_i} - \upsilon_{i,(m_i,\rho_i+1)}\right) \tag{118}$$

$$A_{zi} = \begin{bmatrix} -c_{i1} - l_{i1} & \hat{b}_{i,m_i} & 0 & \dots & 0 \\ -\hat{b}_{i,m_i} & -c_{i2} - l_{i2}\left(\frac{\partial \alpha_{i,1}}{\partial y_i}\right)^2 & 1 + \sigma_{i,(2,3)} & \dots & \sigma_{i,(2,\rho_i)} \\ 0 & -1 - \sigma_{i,(2,3)} & -c_{i3} - l_{i3}\left(\frac{\partial \alpha_{i,2}}{\partial y_i}\right)^2 & \dots & \sigma_{i,(3,\rho_i)} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & -\sigma_{i,(2,\rho_i)} & -\sigma_{i,(3,\rho_i)} & \dots & -c_{i\rho_i} - l_{i\rho_i}\left(\frac{\partial \alpha_{i,(\rho_i-1)}}{\partial y_i}\right)^2 \end{bmatrix}$$

Box II.

$$\mu^* = \min_{1\le i\le N} \sqrt{\frac{\sqrt{((1+k_{i0})k_{i6} + (k_{i3}+k_{i4})k_{i5})^2 + 4k_{i4}k_{i5}\beta} + ((1+k_{i0})k_{i6} + (k_{i3}+k_{i4})k_{i5})}{2k_{i4}k_{i5}}}$$

Box III.

with

$$\alpha_{i,1} = \hat{p}_i\bar{\alpha}_{i,1} \tag{119}$$

$$\bar{\alpha}_{i,1} = -c_{i1}z_{i,1} - l_{i1}z_{i,1} - \xi_{i,(0,2)} - \bar{\delta}_i^{\mathrm{T}}\hat{\theta}_i \tag{120}$$

$$\begin{aligned}\alpha_{i,2} &= -\hat{b}_{i,m_i}z_{i,1} - \left[c_{i2} + l_{i2}\left(\frac{\partial\alpha_{i,1}}{\partial y_i}\right)^2\right]z_{i,2} + \bar{B}_{i,2} \\ &\quad + \frac{\partial\alpha_{i,1}}{\partial\hat{p}_i}\dot{\hat{p}}_i + \frac{\partial\alpha_{i,1}}{\partial\hat{\theta}_i}\Gamma_i\tau_{i,2}\end{aligned} \tag{121}$$

$$\begin{aligned}\alpha_{i,q} &= -z_{i,(q-1)} - \left[c_{iq} + l_{iq}\left(\frac{\partial\alpha_{i,(q-1)}}{\partial y_i}\right)^2\right]z_{i,q} + \bar{B}_{i,q} \\ &\quad + \frac{\partial\alpha_{i,(q-1)}}{\partial\hat{p}_i}\dot{\hat{p}}_i + \frac{\partial\alpha_{i,(q-1)}}{\partial\hat{\theta}_i}\Gamma_i\tau_{i,q} \\ &\quad - \left(\sum_{k=2}^{q-1} z_{i,k}\frac{\partial\alpha_{i,(k-1)}}{\partial\hat{\theta}_i}\right)\Gamma_i\frac{\partial\alpha_{i,(q-1)}}{\partial y_i}\delta_i \\ &\quad q = 3,\dots,\rho_i\end{aligned} \tag{122}$$

$$\begin{aligned}\bar{B}_{i,q} &= \frac{\partial\alpha_{i,(q-1)}}{\partial y_i}(\xi_{i,(0,2)} + \delta_i^T\hat{\theta}_i) + \frac{\partial\alpha_{i,(q-1)}}{\partial\Xi_i}(A_{i,0}\Xi_i \\ &\quad + \Phi_i(y_i)) + \frac{\partial\alpha_{i,(q-1)}}{\partial\xi_{i,0}}(A_{i,0}\xi_{i,0} + k_iy_i) + k_{i,q} \\ &\quad \times v_{i,(m_i,1)} + \sum_{j=1}^{m_i+q-1}\frac{\partial\alpha_{i,(q-1)}}{\partial\lambda_{i,j}}(-k_{i,j}\lambda_{i,1} + \lambda_{i,(j+1)})\end{aligned} \tag{123}$$

$$\tau_{i,q} = \tau_{i,(q-1)} - \frac{\partial\alpha_{i,(q-1)}}{\partial y_i}\delta_i z_{i,q} \tag{124}$$

$$\begin{aligned}\tau_{i,1} &= (\delta_i - \hat{p}_i\bar{\alpha}_{i,1}e_{(n_i+m_i+1),1})z_{i,1} \\ &\quad q = 2,\dots,\rho_i,\ i = 1,\dots,N.\end{aligned} \tag{125}$$

Parameter update laws:

$$\dot{\hat{p}}_i = -\gamma_i'\operatorname{sgn}(b_{i,m_i})\bar{\alpha}_{i,1}z_{i,1} \tag{126}$$

$$\dot{\hat{\theta}}_i = \Gamma_i\tau_{i,\rho_i} \tag{127}$$

where $\hat{\theta}_i$, $\hat{p}_i$, Γ_i and $c_{iq}, l_{iq}, \gamma_i', q = 1,\dots,\rho_i, i = 1,\dots,N$ are defined as in Section 3.2.

4.4. Stability analysis

The ith subsystem (93) and (94) subject to local controller (118) is characterized by

$$\begin{aligned}\dot{z}_i &= A_{zi}z_i + W_{\epsilon i}\epsilon_{i,2} + W_{\theta i}^{\mathrm{T}}\tilde{\theta}_i - b_{i,m_i}\bar{\alpha}_{i,1}\tilde{p}_ie_{\rho_i,1} \\ &\quad + W_{\epsilon i}\left[\sum_{j=1}^N \nu_{ij}e_1^{\mathrm{T}}f_{hi,j}(h_{i,j},x_{j,1}) + \sum_{j=1}^N\mu_{ij}e_1^{\mathrm{T}}f_{gi,j}(g_{i,j},y_j)\right]\end{aligned} \tag{128}$$

where $z_i(t) = [z_{i,1}, z_{i,2},\dots,z_{i,\rho_i}]^{\mathrm{T}}$, A_{zi}, $W_{\epsilon i}$, $W_{\theta i}$ are defined as in Box II, (47) and (48).

To study (128), we consider a function V_{ρ_i} defined as:

$$V_{\rho_i} = \sum_{q=1}^{\rho_i}\left(\frac{1}{2}(z_{i,q})^2 + \frac{1}{l_{iq}}\epsilon_i{}^{\mathrm{T}}P_i\epsilon_i\right) + \frac{1}{2}\tilde{\theta}_i^{\mathrm{T}}\Gamma_i^{-1}\tilde{\theta}_i + \frac{|b_{i,m_i}|}{2\gamma_i'}\tilde{p}_i^2. \tag{129}$$

Following similar procedures to (50), using (110) and (111) and the designed controllers (118)–(127), it can be shown that the derivative of V_{ρ_i} satisfies

$$\begin{aligned}\dot{V}_{\rho_i} &= \sum_{q=1}^{\rho_i} z_{i,q}\dot{z}_{i,q} - \tilde{\theta}_i^{\mathrm{T}}\Gamma^{-1}\dot{\hat{\theta}}_i - \frac{|b_{i,m_i}|}{\gamma_i'}\tilde{p}_i\dot{\hat{p}}_i - \sum_{q=1}^{\rho_i}\frac{1}{l_{iq}}\|\epsilon_i\|^2 \\ &\quad - 2\sum_{q=1}^{\rho_i}\frac{1}{l_{iq}}k_i^{\mathrm{T}}P_i\epsilon_i\left(\sum_{j=1}^N\nu_{ij}e_1^{\mathrm{T}}h_{i,j}(x_{j,1}) + \sum_{j=1}^N\mu_{ij}e_1^{\mathrm{T}}g_{i,j}(y_j)\right) \\ &\le -\sum_{q=1}^{\rho_i}c_{iq}(z_{i,q})^2 - \sum_{q=1}^{\rho_i}\frac{1}{4l_{iq}}\|\epsilon_i\|^2 \\ &\quad + \sum_{q=1}^{\rho_i}\frac{8}{l_{iq}}\|k_i^{\mathrm{T}}P_i\|^2L_{1,i} + \sum_{q=1}^{\rho_i}\frac{1}{l_{iq}}L_{2,i}\end{aligned} \tag{130}$$

where we used Young's Inequality and

$$L_{1,i} = \left(\sum_{j=1}^N\nu_{ij}e_1^{\mathrm{T}}h_{i,j}\right)^2 + \left(\sum_{j=1}^N\mu_{ij}e_1^{\mathrm{T}}g_{i,j}\right)^2 \tag{131}$$

$$\begin{aligned}L_{2,i} &= \left(\sum_{j=1}^N\nu_{ij}e_1^{\mathrm{T}}f_{hi,j}(h_{i,j},x_{j,1})\right)^2 \\ &\quad + \left(\sum_{j=1}^N\mu_{ij}e_1^{\mathrm{T}}f_{gi,j}(g_{i,j},y_j)\right)^2.\end{aligned} \tag{132}$$

Similar to Lemma 1, we have the following useful lemma.

Lemma 2. *The effects of the interactions and unmodeled dynamics are bounded as follows*

$$L_{1,i} \le \left(\max_{1\le,i,j\le N}\{\nu_{ij}^2\} + \max_{1\le,i,j\le N}\{\mu_{ij}^2\}\right)\|\chi\|^2 \tag{133}$$

$$\left(\sum_{j=1}^{N} e_1^{\mathrm{T}} f_{gi,j}(g_{i,j}, y_j)\right)^2 \le k_{i1}\|\chi\|^2 \quad (134)$$

$$\left(\sum_{j=1}^{N} e_1^{\mathrm{T}} f_{hi,j}(h_{i,j}, x_{j,1})\right)^2 \le \left(k_{i2} + k_{i3}(\max_{1\le,i,j\le N}\{\nu_{ij}^2\} + \max_{1\le,i,j\le N}\{\mu_{ij}^2\})\right)\|\chi\|^2 \quad (135)$$

where $\chi = [\chi_1^{\mathrm{T}}, \dots, \chi_N^{\mathrm{T}}]^{\mathrm{T}}$ *and* $\chi_i = [z_i^{\mathrm{T}}, \epsilon_i^{\mathrm{T}}, {h_{i,1}}^{\mathrm{T}}, \dots, {h_{i,N}}^{\mathrm{T}}, {g_{i,1}}^{\mathrm{T}}, \dots, {g_{i,N}}^{\mathrm{T}}]^{\mathrm{T}}$, k_{i2}, k_{i2}, k_{i3} *are positive constants.*

Proof. By following similar analysis to Lemma 1, using Assumption 4.2 and (94), the result can be proved. △

Based on Lemma 2, it follows from (130) that

$$\dot{V}_{\rho_i} \le -\sum_{q=1}^{\rho_i} c_{iq}(z_{i,q})^2 - \sum_{q=1}^{\rho_i}\frac{1}{4l_{iq}}\|\epsilon_i\|^2 + \sum_{q=1}^{\rho_i}\frac{16}{l_{iq}}\|k_i^{\mathrm{T}}P_i\|^2\mu^2\|\chi\|^2 + \sum_{q=1}^{\rho_i}\frac{1}{l_{iq}}((k_{i1}+k_{i2})\mu^2 + 2k_{i3}\mu^4)\|\chi\|^2 \quad (136)$$

where

$$\mu = \max_{1\le i,j\le N}\{\mu_{ij}, \nu_{ij}\} \quad (137)$$

As $f_{hi,j}$ is globally Lipschitz in $x_{j,1}$ according to Assumption 4.2, the derivative of $V_{hi,j}$ with respect to $f_{hi,j}(h_{i,j}, x_{j,1})$ in Assumption 4.3 satisfies

$$\frac{\partial V_{hi,j}}{\partial h_{i,j}} f_{hi,j}(h_{i,j}, x_{j,1}) = \frac{\partial V_{hi,j}}{\partial h_{i,j}} f_{hi,j}(h_{i,j}, 0) + \frac{\partial V_{hi,j}}{\partial h_{i,j}}[f_{hi,j}(h_{i,j}, x_{j,1}) - f_{hi,j}(h_{i,j}, 0)] \le -d_{hij,1}\|h_{i,j}\|^2 + d_{hij,2}\|h_{i,j}\|L_{hij}\|x_{j,1}\| \quad (138)$$

where L_{hij} is a positive constant. Similarly, there exists a positive constant L_{gij} such that

$$\frac{\partial V_{gi,j}}{\partial g_{i,j}} f_{gi,j}(g_{i,j}, y_j) \le -d_{gij,1}\|g_{i,j}\|^2 + d_{gij,2}\|g_{i,j}\|L_{gij}\|y_j\|. \quad (139)$$

We are now at the position to establish the following theorem on the stability of nonlinear systems.

Theorem 3. *Consider the closed-loop adaptive system consisting of the plant* (93) *under Assumptions* 4.1–4.3, *the controller* (118), *the estimators* (126), (127) *and the filters* (103)–(106). *There exists a constant* μ^* *such that for all* $\nu_{ij} < \mu^*$ *and* $\mu_{ij} < \mu^*$, $i, j = 1, 2, \dots, N$, *all the signals in the system are globally uniformly bounded and* $\lim_{t\to\infty} y_i(t) = 0$.

Proof. We define a Lyapunov function for the ith local system

$$V_i = V_{\rho_i} + \sum_{j=1}^{N} l_{hij}V_{hi,j} + \sum_{j=1}^{N} l_{gij}V_{gi,j} \quad (140)$$

where l_{hij} and l_{gij} are positive constants. Computing the time derivative of V_i and using (94), (136)–(139), we have

$$\begin{aligned}
\dot{V}_i &= \dot{V}_{\rho_i} - \sum_{j=1}^{N} l_{hij}d_{hij,1}\|h_{i,j}\|^2 - \sum_{j=1}^{N} l_{gij}d_{gij,1}\|g_{i,j}\|^2 \\
&\quad + \sum_{j=1}^{N} l_{hij}d_{hij,2}\|h_{i,j}\|L_{hij}\|x_{j,1}\| + \sum_{j=1}^{N} l_{gij}d_{gij,2}\|g_{i,j}\|L_{gij}\|y_j\| \\
&\le -\frac{1}{2}c_{i1}z_{i,1}^2 - \sum_{q=2}^{\rho_i} c_{iq}(z_{i,q})^2 - \sum_{q=1}^{\rho_i}\frac{1}{4l_{iq}}\|\epsilon_i\|^2 \\
&\quad + \sum_{q=1}^{\rho_i}\frac{16}{l_{iq}}\|k_i^{\mathrm{T}}P_i\|^2\mu^2\|\chi\|^2 \\
&\quad + \sum_{q=1}^{\rho_i}\frac{1}{l_{iq}}\left((k_{i1}+k_{i2})\mu^2 + 2k_{i3}\mu^4\right)\|\chi\|^2 \\
&\quad - \sum_{j=1}^{N}\left(\frac{1}{2}l_{hij}d_{hij,1}\|h_{i,j}\|^2 + \frac{1}{2}l_{gij}d_{gij,1}\|g_{i,j}\|^2\right) \\
&\quad - \sum_{j=1}^{N}\frac{1}{4}l_{hij}d_{hij,1}\|h_{i,j}\|^2 - \frac{1}{4}c_{i1}z_{i,1}^2 + \sum_{j=1}^{N} l_{hij}d_{hij,2}\|h_{i,j}\|L_{hij}\|z_{j,1}\| \\
&\quad - \sum_{j=1}^{N}\left[\frac{1}{4}l_{hij}d_{hij,1}\|h_{i,j}\|^2 + l_{hij}d_{hij,2}\|h_{i,j}\| \times L_{hij}\left\|\sum_{j=1}^{N}\nu_{ij}e_1^{\mathrm{T}}h_{i,j} + \sum_{j=1}^{N}\mu_{ij}e_1^{\mathrm{T}}g_{i,j}\right\|\right] \\
&\quad - \frac{1}{4}c_{i1}z_{i,1}^2 - \sum_{j=1}^{N}\frac{1}{2}l_{gij}d_{gij,1}\|g_{i,j}\|^2 \\
&\quad + \sum_{j=1}^{N} l_{gij}d_{gij,2}\|g_{i,j}\|L_{gij}\|z_{j,1}\|.
\end{aligned} \quad (141)$$

Taking

$$l_{hij} \le \frac{d_{hij,1}c_{j1}}{4Nd_{hij,2}^2L_{hij}^2}, \quad l_{gij} \le \frac{d_{gij,1}c_{j1}}{2Nd_{gij,2}^2L_{gij}^2} \quad (142)$$

and using Young's inequality, we have

$$\dot{V}_i \le -\beta_i\|\chi_i\|^2 - \frac{1}{4}c_{i1}(z_{i,1})^2 + \left((k_{i4}(k_{i1}+k_{i2}) + k_{i5})\mu^2 + 2k_{i3}k_{i4}\mu^4\right)\|\chi\|^2 - \left(\frac{1}{4}c_{i1}(z_{i,1})^2 - \sum_{j=1}^{N}\frac{1}{4N}c_{j1}(z_{j,1})^2\right) \quad (143)$$

where

$$\beta_i = \min\left\{\frac{c_{i1}}{4}, c_{i2}, \dots, c_{i\rho_i}, \sum_{q=1}^{\rho_i}\frac{1}{4l_{iq}}, \min_{1\le j\le N}\left\{\frac{1}{2}l_{hij}d_{hij,1}, \frac{1}{2}l_{gij}d_{gij,1}\right\}\right\} \quad (144)$$

$$k_{i4} = \sum_{q=1}^{\rho_i}\frac{1}{l_{iq}} \quad (145)$$

$$k_{i5} = \|k_i^{\mathrm{T}}P_i\|^2\sum_{q=1}^{\rho_i}\frac{16}{l_{iq}} + \sum_{j=1}^{N}\frac{4l_{hij}d_{hij,2}^2L_{hij}^2}{d_{hij,1}}. \quad (146)$$

Now we consider the Lyapunov function for the overall decentralized adaptive control system defined as

$$\mu^* = \min_{1\le i\le N} \sqrt{\frac{\sqrt{(k_{i4}(k_{i1}+k_{i2})+k_{i5})^2 + 8k_{i3}k_{i4}\beta} + k_{i4}(k_{i1}+k_{i2}) + k_{i5}}{4k_{i3}k_{i4}}}$$

Box IV.

$$V = \sum_{i=1}^{N} V_i. \tag{147}$$

From (143) and Lemma 2, the derivative of V is given by

$$\dot{V} \le -\sum_{i=1}^{N} \left[\beta - (k_{i4}(k_{i1}+k_{i2}) + k_{i5})\,\mu^2 - 2k_{i3}k_{i4}\mu^4\right] \|\chi\|^2 - \frac{1}{4}\sum_{i=1}^{N} c_{i1}(z_{i,1})^2 \tag{148}$$

where

$$\beta = \frac{\min_{1\le i\le N} \beta_i}{N}. \tag{149}$$

By taking μ^* in Box IV, we have $\dot{V} \le -\frac{1}{4}\sum_{i=1}^{N} c_{i1}(z_{i,1})^2$ for all $\nu_{ij} < \mu^*$ and $\mu_{ij} < \mu^*$. This implies that $z_i, \hat{p}_i, \hat{\theta}_i, \hat{\epsilon}_i$ are bounded. Because of the boundedness of y_i, variables $\upsilon_{i,k}$, $\xi_{i,0}$ and Ξ_i are bounded as $A_{i,0}$ is Hurwitz. Following similar analysis to Section 3, states ζ_i associated with the zero dynamics of the ith subsystem are bounded. This concludes the proof of Theorem 3 that all the signals in the system are globally uniformly bounded. By applying the LaSalle–Yoshizawa theorem, it further follows that $\lim_{t\to\infty} y_i(t) = 0$ for arbitrary initial $x_i(0)$. △

Remark 5. The transient performance for system output $y_i(t)$ in terms of both L_2 and L_∞ norms can also be obtained as in Theorem 2.

5. Illustrative examples

5.1. Linear systems

To verify our results by simulation, we consider interconnected system with two subsystems as described in Box I (i.e. $N = 2$). The transfer function of each local subsystem is $G_i(s) = \frac{1}{s(s+a_i)}$, $i = 1, 2$. In the simulation, $a_1 = -1$ and $a_2 = 2$ which are considered to be unknown in controller design and hence require identification. The dynamic interactions are $H_{ij} = \frac{1}{(s+1)^3}$, $\Delta_{ij} = \frac{1}{(s+1)}$ for $i = 1, 2$ and $j = 1, 2$, respectively. The initials of subsystem outputs are set as $y_1(0) = 1$, $y_2(0) = 0.4$.

5.1.1. Verification of Theorem 1

The design parameters are chosen as $k_i = [4, 4]^{\mathrm{T}}$, $i = 1, 2$, $c_{11} = c_{12} = c_{21} = c_{22} = 1$, $l_{11} = l_{12} = 1_{21} = l_{22} = 0.001$. Simulation reveals that in the decoupling case, i.e. $\nu_{ij} = \mu_{ij} = 0$ for $i = 1, 2$ and $j = 1, 2$, the fixed controllers without adaption, i.e. $\Gamma_1 = \Gamma_2 = 0$, give stable systems. But when $\nu_{ij} = \mu_{ij} = 0.7$ for $i = 1, 2$ and $j = 1, 2$, these fixed local controllers cannot stabilize the interconnected system, due to the presence of interactions and unmodeled dynamics. With the presented adaptation mechanism on by choosing $\Gamma_1 = \Gamma_2 = 0.1$, the results are given in Figs. 4 and 5. Clearly, the system is now stabilized and the outputs of both subsystems converge to zero. This verifies that the proposed scheme is effective in handling interactions and unmodeled dynamics as stated in Theorem 1.

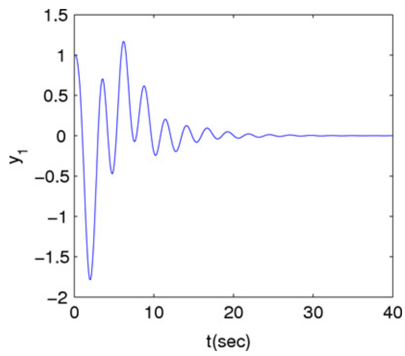

Fig. 4. Linear subsystem output y_1.

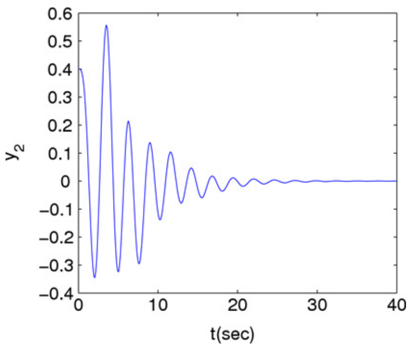

Fig. 5. Linear subsystem output y_2.

5.1.2. Verification of Theorem 2

We still consider the interconnected system with parameters given above. The initial values $z_{i,q}(0)$ for $i = 1, 2$ and $q = 2$ are set to 0 by properly initializing filters according to Eq. (89). In our case, $\upsilon_{i,(0,2)}(0) = \alpha_{i,(0,2)}(0)$ for $i = 1, 2$. The design parameters l_{ij} are fixed as 0.001 and $c_{12} = c_{22} = 1$, which are the same as the above. We now consider the following two cases:

(1) **Effects of parameters c_{i1}**
The effects of changing design parameters c_{i1} stated in Theorem 2 are now verified by choosing $c_{11} = c_{21} = 1$ and 3 respectively. The corresponding initials $\upsilon_{i,(0,2)}(0)$ are selected as $\upsilon_{1,(0,2)}(0) = -1.001$, $\upsilon_{2,(0,2)}(0) = -0.4004$, and $\upsilon_{1,(0,2)}(0) = -3.001$, $\upsilon_{2,(0,2)}(0) = -1.2004$ for the two sets of choices of c_{i1}. In the verification, we fix $\Gamma_1 = \Gamma_2 = 0.1$. The outputs of the two subsystem outputs y_1, y_2 are compared in Figs. 6 and 7. Obviously, the L_2 norms of the outputs decrease as c_{i1} for $i = 1, 2$ increase.

(2) **Effects of parameters Γ_i**
We now fix c_{i1} at 1 for all $i = 1, 2$ and choose initials $\upsilon_{1,(0,2)}(0) = -1.001$ and $\upsilon_{2,(0,2)}(0) = -0.4004$. For comparison, Γ_i are set as 0.1 and 1, respectively for $i = 1, 2$. The subsystem outputs y_1, y_2 are compared in Figs. 8 and 9. Clearly, the transient tracking performances are found significantly improved by increasing Γ_i.

5.2. Nonlinear systems

To further verify the effectiveness of our proposed scheme applied to nonlinear interconnected systems, we consider two

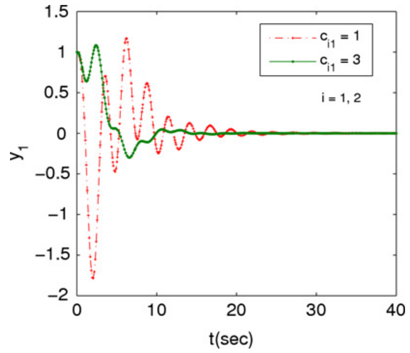

Fig. 6. Output y_1 with different c_{i1}.

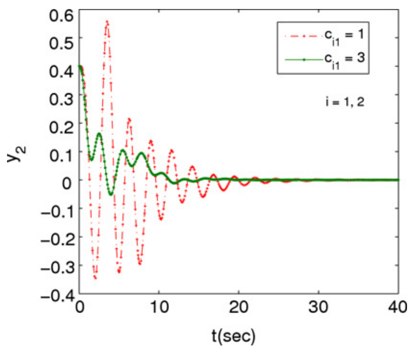

Fig. 7. Output y_2 with different c_{i1}.

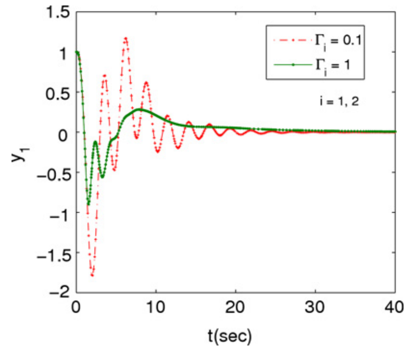

Fig. 8. Output y_1 with different Γ_i.

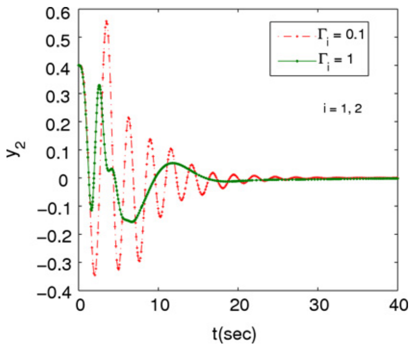

Fig. 9. Output y_2 with different Γ_i.

nonlinear interconnected subsystems with $n_i = 2$, for $i = 1, 2$ as described in (93) and (94), where $\Phi_1 = [0, (y_1)^2]^{\mathrm{T}}$, $\Phi_2 = [0, (y_2)^2 + y_2]^{\mathrm{T}}$, $\sigma_i(y_i) = 1$. In simulation, $a_1 = -1$, $a_2 = 2$, $b_1 = 1$, $b_2 = 2$, $h_{i,j}$ and $g_{i,j}$ given in (150) and (151) below are all considered to be unknown in controller design. All the initials are set as 0 except that subsystem outputs $y_1(0) = 1$, $y_2(0) = 0.4$.

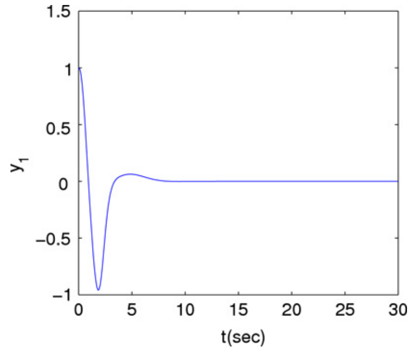

Fig. 10. Nonlinear subsystem output y_1.

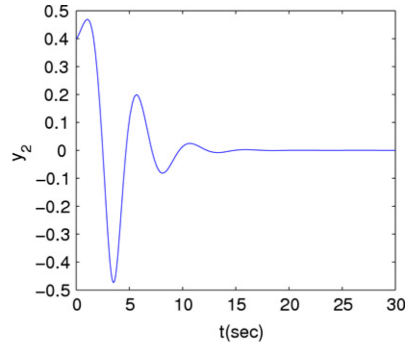

Fig. 11. Nonlinear subsystem output y_2.

$$\dot{h}_{i,j} = \begin{bmatrix} -3 & 1 \\ -2.25 & 0 \end{bmatrix} h_{i,j} + \begin{bmatrix} \dfrac{1-\mathrm{e}^{-h_{i,j}(1)}}{1+\mathrm{e}^{-h_{i,j}(1)}} \\ \dfrac{1-\mathrm{e}^{-h_{i,j}(2)}}{1+\mathrm{e}^{-h_{i,j}(2)}} \end{bmatrix} + \begin{bmatrix} \sin(h_{i,j(1)}) \\ \sin(h_{i,j(2)}) \end{bmatrix} x_{j,1} \tag{150}$$

$$\dot{g}_{i,j} = \begin{bmatrix} -4 & 1 \\ -4 & 0 \end{bmatrix} g_{i,j} + \begin{bmatrix} \dfrac{1-\mathrm{e}^{-g_{i,j}(1)}}{1+\mathrm{e}^{-g_{i,j}(1)}} \\ \dfrac{1-\mathrm{e}^{-g_{i,j}(2)}}{1+\mathrm{e}^{-g_{i,j}(2)}} \end{bmatrix} + \begin{bmatrix} \dfrac{y_j}{|\ln y_j| + 2} \\ y_j \end{bmatrix}. \tag{151}$$

5.2.1. *Verification of* Theorem 3

When $\nu_{ij} = \mu_{ij} = 0.01$ for $i = 1, 2$ and $j = 1, 2$, the design parameters are chosen as $k_i = [4, 4]^{\mathrm{T}}$, $i = 1, 2$, $c_{11} = c_{12} = c_{21} = c_{22} = 0.5$, $l_{11} = l_{12} = 1_{21} = l_{22} = 0.001$. With the adaptation mechanism on by choosing $\gamma_1 = \gamma_2 = 1$; $\Gamma_1 = \Gamma_2 = 1 \times I_2$, the system outputs y_1, y_2 are illustrated in Figs. 10 and 11. These results verify that the system can be stabilized and the outputs of both nonlinear subsystems converge to zero in the presence of interactions and unmodeled dynamics.

6. Conclusion

In this paper, decentralized adaptive output feedback stabilization of interconnected systems with dynamic interactions depending on both subsystem inputs and outputs is considered. Especially, this paper presents a solution to decentrally stabilize systems with interactions directly depending on subsystem inputs for the first time, when the backstepping technique is used. By using the standard backstepping technique, totally decentralized adaptive controllers are designed. In our design, there is no a priori information on parameters of subsystems and thus they can be allowed totally uncertain. It is established that the proposed decentralized controllers can ensure the overall system globally asymptotically stable. Furthermore, the L_2 and L_∞ norms of the system outputs are also shown to be bounded by functions of design parameters. This implies that the transient system performance can be adjusted by choosing suitable design parameters. Simulation results illustrate the effectiveness of our proposed scheme.

Note that some robust control schemes based on backstepping approaches are available for systems with certain input unmodeled dynamics, see for example Krstic, Sun, and Kokotovic (1996). Such a class of unmodeled dynamics is different from what considered in this paper. We feel that it is worthy to explore such types of input unmodeled dynamics and interactions in the context of decentralized adaptive control.

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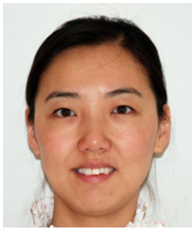
Changyun Wen received his B.Eng. from Xi'an Jiaotong University in China in July 1983 and Ph.D. from the University of Newcastle in Australia in February 1990. From August 1989 to August 1991, he was a Postdoctoral Fellow at the University of Adelaide, Australia. Since August 1991, he has been with the School of Electrical and Electronic Engineering at Nanyang Technological University, where he is currently a Full Professor.

Currently, he is an Associate Editor of Automatica and a Member of the Editorial Board of Journal of Control and Decision. He also served the IEEE Transactions on Automatic Control as an Associate Editor from January 2000 to December 2002. He has been actively involved in organizing international conferences playing the roles of General Chair, General Co-Chair, Technical Program Committee Chair, Program Committee Member, General Advisor, Publicity Chair and so on. He received the IES Prestigious Engineering Achievement Award 2005 from the Institution of Engineers, Singapore (IES) in 2005.



Jing Zhou received her B.Eng from Northwestern Polytechnical University in China in July 2000 and Ph.D. from Nanyang Technological University in Singapore in February 2006. From March 2005 to March 2007, she was a research fellow at Nanyang Technological University, Singapore. She is currently a Postdoctoral Fellow at Norwegian University of Science and Technology, Norway. Her diligent research work has been widely recognized and published in internationally refereed journals and conference proceedings. Her research interests include adaptive control, robust control, nonlinear control, control application in petroleum industry, and actuator and sensor nonlinearities.

Wei Wang received her B.Eng. degree in Electrical Engineering and Automation from Beijing University of Aeronautics and Astronautics, China, in July 2005 and M.Sc. degree in Radio Frequency Communication Systems with Distinction from University of Southampton, England, in July 2007. She is currently a Ph.D. candidate in School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore. Her research interests include adaptive control, nonlinear control systems, fault detection, fault tolerant control and combining control techniques with communication problems.