

Data Driven Multiagent Systems Consensus Tracking Using Model Free Adaptive Control

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Abstract: This paper proposes a distributed model free adaptive control scheme that can be applied to multi-agent systems to solve consensus tracking problem under the fixed communication topology. The agent's dynamics are modeled by unknown nonlinear functions. In addition, the desired consensus trajectory is only accessible to a subset of the followers. By introducing the concept pseudo-partial derivative, the dynamical linearization model of each agent has been established and then the distributed model free adaptive control scheme has been designed to enable all agents to achieve the desired trajectories. The main feature of the approach is that consensus tracking control can be solved only depending on the I/O data of each agent. By the theoretical analysis, it is shown that tracking error is convergent and output and control input sequences are bounded. An illustrative example is given to demonstrate the effectiveness of the proposed design methods.

Key Words: Model Free Adaptive Control; Multi-agent systems; Consensus tracking; Data driven design

1 INTRODUCTION

Recently, distributed coordination of multiagent systems have attracted considerable attention from more and more researchers due to its broad applications in autonomous underwater vehicles, mobile robots, automated highway systems, satellite formation, and so on. As a result, many theoretical results have been established for cooperative control of multiagent systems [1], [2]. Consensus is an important issue of multiagent systems coordination problems. The task of consensus is to design appropriate control strategies or protocols based on local information such that the group of dynamic agents can reach an agreement on certain quantities of interest. In a consensus realization, the control action of an agent only depends on the information received or measured from its neighborhood. Since the control law is a kind of distributed algorithm, it is more robust and scalable compared to centralized control algorithms.

There has been considerable effort in solving the multiagent consensus problem [3-10]. In [3], the average consensus of networks of first-order integrator agents with the directed information communication is considered, and the impact of network delay is also investigated. In [4], multiagent consensus problem for multiagent systems with nonlinear dynamics and switching communication links is analyzed by the contraction property. In [5], an improved condition for the consensus of multiagent systems with the

switching directed graph topology is provided, which only requires a spanning tree in the union of interaction graphs. In [6], a consensus protocol for multiagent systems with an active leader is proposed. It is demonstrated that every agent can track the leader's trajectory even if the partial velocity information of the leader agent is unknown. In [7], using the view of optimal control, a nonlinear consensus approach is proposed by designing the individual objective of each agent. In [8], consensus problem is considered for agents with the double-integrator dynamics. In [9, 10], consensus over random networks or stochastically switching graph is considered. It is shown the almost sure consensus can be achieved in such kind of probabilistic settings. For the state of art of multiagent consensus research, the readers are referred to [11] and [12].

In practical multiagent systems, almost all the agents contain nonlinearities, and it is difficult to obtain the exact system model. Therefore, the study of consensus problems for a group of agents with unknown nonlinear dynamics is an interesting topic. In [13], an adaptive control method is proposed to the consensus control for uncertain nonlinear multiagent systems. However, the assumption of linearity on control input term is necessary. In [14-16], the problems of adaptive NN consensus control of nonlinear multiagent systems have been studied. However, the external testing signals and some training processes are necessary for the neural networks based nonlinear adaptive control. Besides, iterative learning control is an effective consensus control or formation control approaches for nonlinear multiagent systems with unknown dynamics [17-19]. Thus, this approach suffers from the assumption that coordination problems are repeatable or require periodic executions.

Model free adaptive control (MFAC) is an effective approach for general discrete time nonlinear systems with

This work was supported by the National Natural Science Foundation of China (Nos. 61573129, 61203065, 61120106009, 61433002), the Fundamental Research Funds for the Universities of Henan Province, the program of Key Young Teacher of Henan Polytechnic University and the Doctoral Fund Program of Henan Polytechnic University (B2012-003).

unknown dynamics [20-22]. Instead of identifying a more or less nonlinear model of a plant, an equivalent dynamical linearization model is built along the dynamic operation points of the closed-loop system using a new dynamic linearization technique with a novel concept called pseudo-partial derivative (PPD). The time-varying PPD could be estimated merely using the I/O measurement data of a controlled plant. This paper addresses consensus problem of nonlinear multiagent systems with unknown dynamics using MFAC approach.

The remainder of this paper is organized as follows. Section 2 introduces some preliminary results and the problem formulation. Section 3 provides the proposed multiagent consensus tracking algorithm and analyzes the system performance. An illustrative example is given in Section 4. Section 5 concludes this paper and discusses the future work.

2 Preliminaries and Problem Formulation

2.1 Preliminaries

The set of real numbers is denoted by R . For any given matrix $A \in R^{n \times n}$, $\|A\|$ is a matrix norm, $\mu(A)$ is the spectral radius of A . I is the identity matrix with appropriate dimension. $\text{diag}(\cdot)$ donates the diagonal matrix. Graph theory is an instrumental tool to describe the communication topology in the multiagent systems, the basic terminologies in graph theory are briefly introduced below.

Let $\mathcal{G}=(\mathcal{V},\mathcal{E},\mathcal{A})$ be a weighted directed graph with the set of vertices $\mathcal{V}=\{1,2,\dots,N\}$, the set of edges $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$, and the adjacency matrix $\mathcal{A}$. Let $\mathcal{V}$ also be the index set representing the agents in the systems. A direct edge from i to j is denoted by an ordered pair $(i,j) \in \mathcal{E}$, which means that agent j can receive information from agent i . In this case, i is called the parent of j , and j is the child of i . The neighborhood of the i th agent is denoted by the set $N_i = \{j \in \mathcal{V} | (j,i) \in \mathcal{E}\}$. $\mathcal{A} = (a_{i,j}) \in R^{N \times N}$ is the weighted adjacency matrix of $\mathcal{G}$. In particular, $a_{i,i} = 0, a_{i,j} = 1$ if $(j,i) \in \mathcal{E}$, and $a_{i,j} = 0$ otherwise. The in-degree of vertex i is defined as $d_i^{\text{in}} = \sum_{j=1}^N a_{i,j}$, and the Laplacian of $\mathcal{G}$ is defined as $L = \mathcal{D} - \mathcal{A}$, where $\mathcal{D} = \text{diag}(d_1^{\text{in}}, d_2^{\text{in}}, \dots, d_N^{\text{in}})$. A spanning tree is a directed graph, whose vertices have exactly one parent except for one vertex, which is called the root who has no parent. We say that a graph contains or has a spanning tree if $\mathcal{V}$ and a subset of $\mathcal{E}$ can form a spanning tree.

2.2 Problem formation

In the consensus literature, the consensus problem is usually studied for a group of identical agents. However, heterogeneity is the nature of multiagent systems. Even for the same type of agents with the similar structures, it is impossible that they share the identical parameters. Hence,

consensus problem for heterogeneous agents is more practical.

This paper considers a heterogeneous multiagent system consisting of N agents. Their interaction topology is described by $\mathcal{G}=(\mathcal{V},\mathcal{E},\mathcal{A})$. The i th agent is governed by the following nonlinear dynamics

$$y_i(k+1) = f_i(y_i(k), u_i(k)), i=1,2,\dots,N, \quad (1)$$

where $u_i(k) \in R^1$ is control input at time instant k , $y_i(k) \in R^1$ is measurement output, $f_i(\cdot)$ is an unknown nonlinear function. The information available is the output signal of each agent.

Assume the desired consensus tracking trajectory is denoted by $y_d(k)$, which is only accessible to a subset of agents. Thus, we can view the desired trajectory as a virtual leader, and index it by vertex 0 in the graph representation. In this case, the complete information flow of the whole interaction topology can be described as $\bar{\mathcal{G}}=(\mathcal{V} \cup \{0\}, \bar{\mathcal{E}}, \bar{\mathcal{A}})$, where $\bar{\mathcal{E}}$ is the edge set and $\bar{\mathcal{A}}$ is the weighted adjacency matrix of $\bar{\mathcal{G}}$.

To facilitate our analysis, the following assumptions for nonlinear dynamics are used.

Assumption 1: The partial derivative of $f_i(\cdot)$ with respect to control input $u_i(k)$ is continuous.

Assumption 2: The agent (1) is generalized Lipschitz, that is, $|\Delta y_i(k+1)| \leq b |\Delta u_i(k)|$ for any k and $\Delta u_i(k) \neq 0$ wit $\Delta y_i(k+1) = y_i(k+1) - y_i(k)$, $\Delta u_i(k) = u_i(k) - u_i(k-1)$ and b is a positive constant.

Remark 1: The above two assumptions are reasonable and acceptable for practical nonlinear multiagent systems. Assumption 1 is a typical condition of control system design. Assumption 2 supplies a bound limitation on the change rate of the system output driven by the changes of the control inputs. From the energy point of view, the energy change rate inside a system cannot go to infinity if the changes of the control input energies are in finite altitudes. Many practical multiagent systems, such as mobile robots, unmanned air vehicles, can satisfy the assumption.

Theorem 1 [21]: For the agent i described by system (1) satisfying assumptions A1 and A2, there must exist a $\phi_i(k)$, called pseudo-partial-derivative (PPD), such that if $\Delta u_i(k) \neq 0$, (1) can be described as the following compact form dynamic linearization (CFDL) model

$$\Delta y_i(k+1) = \phi_i(k) \Delta u_i(k), \quad (2)$$

and $|\phi_i(k)| \leq b$.

Proof: See the proof of Theorem 1 in [21].

Let $\xi_i(k)$ denotes the information available for the i th agent. It is defined as

$$\xi_i(k) = \sum_{j \in N_i} a_{ij} (y_i(k) - y_j(k)) + d_i (y_d(k) - y_i(k)), \quad (3)$$

where a_{ij} is the (j,i) th entry in the adjacency matrix A , N_i is the neighborhood set of the i th agent. If agent i can

access the desired trajectory, $d_i = 1$, i.e., there is an edge for the virtual leader to the i th agent or $\{0, i\} \in \bar{\mathcal{E}}$. Otherwise, $d_i = 0$.

Define the tracking errors $e_i(k) = y_d(k) - y_i(k)$, the control objective of this paper is to design an appropriate control law only depending on the I/O data of the agents, such that the outputs from all agents converge to the desired trajectory $y_d(k)$ when only some of agents can access the desired trajectory.

Assumption 3: The communication graph $\bar{\mathcal{G}}$ contains a spanning tree with the (virtual) leader being the root.

Remark 2: Assumption 3 is a necessary communication requirement for the solvability of the consensus problem. If there is an isolated agent, it is impossible for that agent to follow the leader's trajectory as it does not even know the control objective. It is noted that the original communication graph $\mathcal{G}$ does not necessarily contain a spanning tree.

Assumption 4: The PPD $\phi_i(k) > \varsigma, i = 1, 2, 3, \dots, N$ (or $\phi_i(k) < -\varsigma$) is hold for all k , where ς is an arbitrarily small positive constant. Without loss of generality, we assume $\phi_i(k) > \varsigma$ in this paper.

3 Main Results

To solve the consensus tracking problem, we design the following distributed MFAC algorithms

$$\hat{\phi}_i(k) = \hat{\phi}_i(k-1) + \frac{\eta \Delta u_i(k-1)}{\mu + |\Delta u_i(k-1)|^2} (\Delta y_i(k) - \hat{\phi}_i(k-1) \Delta u_i(k-1)) \quad (4)$$

$$\hat{\phi}_i(k) = \hat{\phi}_i(1), \text{ if } |\hat{\phi}_i(k)| \leq \varepsilon \text{ or } \text{sign}(\hat{\phi}_i(k)) \neq \text{sign}(\hat{\phi}_i(1)), \quad (5)$$

$$u_i(k) = u_i(k-1) + \frac{\rho \hat{\phi}_i(k)}{\lambda + |\hat{\phi}_i(k)|^2} \xi_i(k). \quad (6)$$

where η, ρ are the step-size, $\mu > 0, \lambda > 0$ are weight factors. $\hat{\phi}_i(k)$ is the estimated value of $\phi_i(k)$, $\hat{\phi}_i(1)$ is the initial value of $\hat{\phi}_i(k)$, and ε is a small positive constant.

Remark 3: we can see that distributed MFAC schemes have no relations with any explicit or implicit model dynamics and structural information of the plant, and PPD parameters are estimated just by using the measured I/O data. Hence, it is a data driven control approach for multiagent systems consensus tracking problem.

The following lemma is used for the convergence analysis in the main result.

Lemma 1 [23]. For any given matrix $A \in R^{n \times n}$, there exists any $\zeta > 0$ and at least one matrix norm $\|A\|$ such that $\|A\| < \mu(A) + \zeta$.

Now, the stability of the MFAC consensus scheme is given in the following theorem.

Theorem 2: Consider the multiagent system (1) satisfying Assumption 1-4, and let the distributed MFAC

schemes (4)-(6) are used. The desired trajectory $y_d(k)$ is a constant, that is $y_d(k) = y^* = \text{const}$. If we choose ρ satisfying $0 < m_{ij}\rho < 1$ for all $i = 1, 2, \dots, N$, where $m_{ij} (i = 1, 2, \dots, N, j = 1, 2, \dots, N)$ is the elements of matrix M with $M = L + D$, L is the Laplacian matrix of graph $\mathcal{G}$ and $D = \text{diag}(d_1, d_2, \dots, d_N)$, then there exists a $\lambda_{\min} > 0$ and $\lambda > \lambda_{\min}$ such that the tracking errors $e_i(k)$ converges to 0 as $k \rightarrow \infty$ for all $i = 1, 2, \dots, N$.

Proof. We first prove the PPD estimated value $\hat{\phi}_i(k)$ is bounded. Define $\tilde{\phi}_i(k) = \hat{\phi}_i(k) - \phi_i(k)$ as the error of PPD estimation. From theorem 1, we have $\Delta y_i(k) = \phi_i(k-1) \Delta u_i(k-1)$. Subtracting $\phi_i(k)$ from both sides of the parameter estimation algorithm (4) gives

$$\tilde{\phi}_i(k) = \left(1 - \frac{\eta \Delta u_i(k-1)^2}{\mu + |\Delta u_i(k-1)|^2} \right) \tilde{\phi}_i(k-1) + \phi_i(k-1) - \phi_i(k). \quad (7)$$

Taking absolute value on both sides of (7), we have

$$|\tilde{\phi}_i(k)| \leq \left| 1 - \frac{\eta \Delta u_i(k-1)^2}{\mu + |\Delta u_i(k-1)|^2} \right| |\tilde{\phi}_i(k-1)| + |\phi_i(k-1) - \phi_i(k)|. \quad (8)$$

Since $|\Delta u_i(k)| \neq 0$, by properly selecting η, μ , for example $0 < \eta \leq 1$ and $\mu \geq 0$, there exists a constant q_1 such that

$$0 < \left| 1 - \frac{\eta \Delta u_i(k-1)^2}{\mu + |\Delta u_i(k-1)|^2} \right| \leq q_1 < 1 \quad (9)$$

holds. The property $|\phi_i(k)| \leq b$ in Theorem 1 leads to $|\phi_i(k-1) - \phi_i(k)| \leq 2b$. From (8) and (9) we have

$$\begin{aligned} |\tilde{\phi}_i(k)| &\leq q_1 |\tilde{\phi}_i(k-1)| + 2b \\ &\leq q_1^2 |\tilde{\phi}_i(k-2)| + 2q_1 b + 2b \\ &\leq \dots \leq q_1^{k-1} |\tilde{\phi}_i(1)| + \frac{2b(1-q_1^{k-1})}{1-q_1}, \end{aligned} \quad (10)$$

which implies that $\tilde{\phi}_i(k)$ is bounded, then the boundedness of $\hat{\phi}_i(k)$ is also guaranteed as $\phi_i(k)$ is bounded.

In the following, we prove the convergence of tracking errors.

From (3), we can rewrite the distributed measurement output $\xi_i(k)$ in terms of tracking errors as

$$\xi_i(k) = \sum_{j \in N_i} a_{ij} (e_i(k) - e_j(k)) + d_i e_i(k). \quad (11)$$

Define the following column stack vectors

$$\begin{aligned} \mathbf{y}(k) &= [y_1(k) \ y_2(k) \ \dots \ y_N(k)]^T, \\ \mathbf{e}(k) &= [e_1(k) \ e_2(k) \ \dots \ e_N(k)]^T, \\ \boldsymbol{\xi}(k) &= [\xi_1(k) \ \xi_2(k) \ \dots \ \xi_N(k)]^T, \\ \mathbf{u}(k) &= [u_1(k) \ u_2(k) \ \dots \ u_N(k)]^T. \end{aligned}$$

Consequently, (11) can be described as the following

compact form

$$\xi(k) = (L + D)\mathbf{e}(k). \quad (12)$$

According to (12), the distributed MFAC law (6) can be rewritten as

$$\mathbf{u}(k) = \mathbf{u}(k-1) + H_1(k)(L + D)\mathbf{e}(k), \quad (13)$$

where

$$H_1(k) = \text{diag} \left(\frac{\rho \hat{\phi}_1(k)}{\lambda + |\hat{\phi}_1(k)|^2}, \frac{\rho \hat{\phi}_2(k)}{\lambda + |\hat{\phi}_2(k)|^2}, \dots, \frac{\rho \hat{\phi}_N(k)}{\lambda + |\hat{\phi}_N(k)|^2} \right)$$

We also can describe the compact form of CFDL model as

$$\mathbf{y}(k+1) = \mathbf{y}(k) + H_\phi(k)\Delta\mathbf{u}(k), \quad (14)$$

where

$$\Delta\mathbf{u}(k) = \mathbf{u}(k) - \mathbf{u}(k-1),$$

$$H_\phi(k) = \text{diag}(\phi_1(k), \phi_2(k), \dots, \phi_N(k)).$$

Substituting (13) into (14), we can obtain

$$\begin{aligned} \mathbf{e}(k+1) &= \mathbf{e}(k) - H_\phi(k)H_1(k)(L + D)\mathbf{e}(k) \\ &= (I - H_\phi(k)H_1(k)(L + D))\mathbf{e}(k) \\ &= (I - H_\phi(k)H_1(k)M)\mathbf{e}(k). \end{aligned} \quad (15)$$

Notice that

$$\begin{aligned} &I - H_\phi(k)H_1(k)M \\ &= \text{diag} \left(1 - \frac{m_{11}\rho\phi_1(k)\hat{\phi}_1(k)}{\lambda + |\hat{\phi}_1(k)|^2}, 1 - \frac{m_{22}\rho\phi_2(k)\hat{\phi}_2(k)}{\lambda + |\hat{\phi}_2(k)|^2}, \dots, 1 - \frac{m_{NN}\rho\phi_N(k)\hat{\phi}_N(k)}{\lambda + |\hat{\phi}_N(k)|^2} \right). \end{aligned}$$

Since $\phi_i(k)$ and $\hat{\phi}_i(k)$ are bounded for all $i = 1, 2, \dots, N$, there exists a bounded constant $\lambda_{\min} > 0$ such that the following inequality holds if $\lambda > \lambda_{\min}$,

$$\begin{aligned} 0 < q_2 &\leq \frac{\phi_i(k)\hat{\phi}_i(k)}{\lambda + |\hat{\phi}_i(k)|^2} \leq \frac{b\hat{\phi}_i(k)}{\lambda + |\hat{\phi}_i(k)|^2} \\ &\leq \frac{b\hat{\phi}_i(k)}{2\sqrt{\lambda}\hat{\phi}_i(k)} < \frac{b}{2\sqrt{\lambda_{\min}}} < 1. \end{aligned} \quad (16)$$

If we choose ρ satisfying $0 < m_{ii}\rho < 1$ for all $i = 1, 2, \dots, N$, then we can obtain the following inequality from (16)

$$0 < 1 - \frac{m_{ii}\rho\phi_i(k)\hat{\phi}_i(k)}{\lambda + |\hat{\phi}_i(k)|^2} \leq 1 - m_{ii}\rho q_2 = q_3 < 1.$$

which implies that $\mu(I - H_\phi(k)H_1(k)M) \leq q_3 < 1$ for all k . Based on lemma 1, there exists $\zeta > 0$ and a matrix norm such that

$$\begin{aligned} \|I - H_\phi(k)H_1(k)M\| &\leq \mu(I - H_\phi(k)H_1(k)M) + \zeta \\ &\leq q_3 + \zeta = q_4 < 1. \end{aligned}$$

Taking norm on both sides of (15) yields

$$\begin{aligned} \|\mathbf{e}(k+1)\| &\leq \|I - H_\phi(k)H_1(k)M\| \|\mathbf{e}(k)\| \\ &\leq q_4 \|\mathbf{e}(k)\| \leq \dots \leq q_4^k \|\mathbf{e}(1)\|, \end{aligned} \quad (17)$$

which indicates that $\lim_{k \rightarrow \infty} |e_i(k)| = 0$ and $\lim_{k \rightarrow \infty} |y_i(k) - y^*| = 0$ for all $i = 1, 2, \dots, N$.

This completes the proof.

Remark 4: It can be seen that the condition in theorem 2 depends on communication graph $\mathcal{G}$ as the m_{ii} is calculated from $L + D$. Hence, theorem 2 reveals the relation between communication topology and convergence property. Under such a condition, we can handle the consensus tracking problem by using distributed MFAC laws.

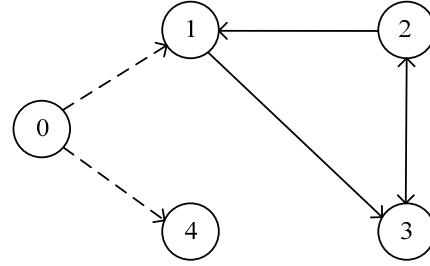


Fig. 1. Communication topology among agents.

4 Illustrative example

In this section, we verify our theoretical result using a network consisting of four follower agents. The leader is indexed by vertex 0. The agent models are governed by

$$\text{agent 1: } y_1(k+1) = \frac{y_1(k)}{1 + y_1^2(k)} + u_1^3(k).$$

$$\text{agent 2: } y_2(k+1) = \frac{y_2(k)}{1 + y_2^3(k)} + u_2^2(k).$$

$$\text{agent 3: } y_3(k+1) = \frac{y_3(k)}{1 + y_3^2(k)} + u_3(k).$$

$$\text{agent 4: } y_4(k+1) = \frac{y_4(k)}{1 + y_4^5(k)} + u_4(k).$$

Notice that the above agents are heterogeneous and all the agent dynamics are different from each other. All dynamic models are unknown, and here they are given just serve as I/O data generator for the systems to be controlled, no any information of them will be included in the MFAC controllers design.

The desired trajectory is

$$y_d(k) = \begin{cases} 2, & 0 < k < 500 \\ 1, & 500 \leq k < 1000 \end{cases}.$$

The information flow of the agents is shown in Fig.1. It is assumed that the information exchange among followers is fixed and directed. In the communication graph, the virtual leader is donated as vertex 0, and it has edges (dash arrows) to agent 1 and 4. Although the communication graph among followers is not connected, the communication graph including the leader contains a spanning tree with the leader being the root. For simplicity, 0-1 weighting is adopted in the adjacency matrix. Thus, the Laplacian for

follower agents is

$$L = \begin{bmatrix} 1 & -1 & 0 & 0 \\ 0 & 1 & -1 & 0 \\ -1 & -1 & 2 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

and $D = \text{diag}(1 \ 0 \ 0 \ 1)$. The diagonal elements of matrix M are $\{2 \ 1 \ 2 \ 1\}$. Select the controller parameters as $\rho = 0.3$, it is obvious that the condition $0 < m_{ii}\rho < 1$ in theorem 2 is satisfied for all $i = 1, 2, 3, 4$, then the consensus tracking is achievable by the MFAC schemes (4)-(6).

In the simulation, the initial conditions are selected as $u_i(1) = 0, \hat{\phi}_i(1) = 2, y_i(1) = 0$ for all agents. The controller parameters is chosen as $\eta = 1, \mu = \lambda = 0.5, \varepsilon = 10^{-4}$. Fig. 2 gives the consensus tracking errors and Fig. 3 gives the output trajectories of all the agents. It is shown that the trajectories of followers have very large deviations from the desired one at the beginning time, thus the tracking errors are gradually reduced by the MFAC controllers, and the desired trajectories can be achieved after time instant $k = 50$. When the desired trajectory is varied at $k = 500$, the perfect tracking can be also obtained after $k = 550$. Hence, the consensus tracking for multiagents can be handled by the proposed MFAC laws. Fig. 4 gives the control input sequences for all agents. It is obvious that the control input sequences are bounded.

5 Conclusions

In this paper, the consensus problem is considered for multiagents systems with nonlinear dynamics. By introducing the concept PPD, the dynamical linearization model of each agent has been established and then the distributed MFAC schemes have been designed to enable all agents to achieve the desired trajectories. It is shown that the approach uses merely the I/O data of agents to design the controller directly. An example for heterogeneous agent system under directed graph is given to demonstrate the effectiveness of the developed design methods. The obtained results not only can significantly extend the MFAC approach to distributed multi-agent systems but also bring novel data driven design for multi-agent systems consensus.

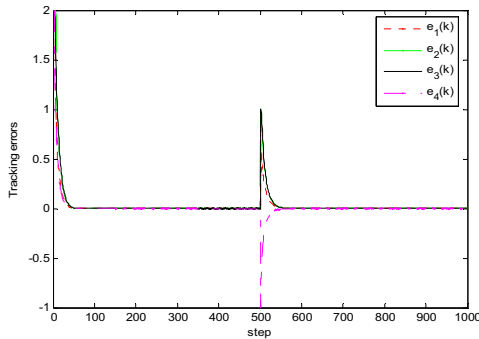


Fig. 2. Consensus tracking errors of multiagents.

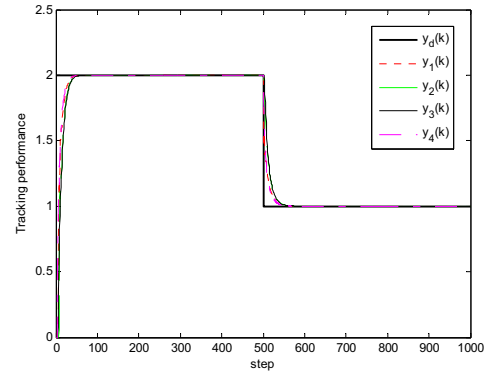


Fig. 3. Tracking performance of all agents.

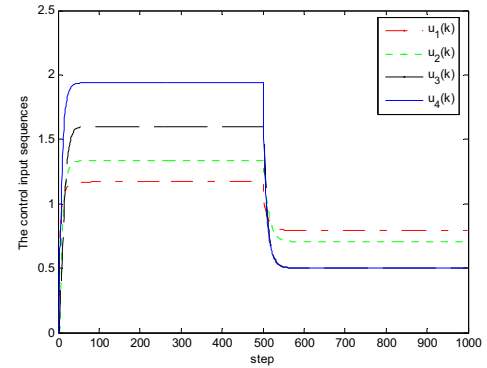


Fig. 4. Control input sequences of all agents

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