Learning-based Robust Bipartite Consensus Control for a Class of Multiagent Systems

Huarong Zhao, Jinjun Shan, *Senior Member, IEEE*, Li Peng, Hongnian Yu, *Senior Member, IEEE*

***Abstract*—This paper studies the robust bipartite consensus problems for heterogeneous nonlinear nonaffine discrete-time multiagent systems (MASs) with fixed and switching topologies against data dropout and unknown disturbances. At first, the controlled system's virtual linear data model is developed by employing the pseudo partial derivative technique, and a distributed combined measurement error function is established utilizing a signed graph theory. Then, an input gain compensation scheme is formulated to mitigate the effects of data dropout in both feedback and forward channels. Moreover, a data-driven learning-based robust bipartite consensus control (LRBCC) scheme based on a radial basis function neural network observer is proposed to estimate the unknown disturbance, using the online input/output data without requiring any information on the mathematical dynamics. The stability analysis of the proposed LRBCC approach is given. Simulation and hardware testing also illustrate the correctness and effectiveness of the designed method.**

***Index Terms*—Multiagent systems, bipartite consensus, data-driven control, data dropout, unknown disturbance, neural networks.**

I. Introduction

IN the past few years, multiagent systems (MASs) research has attracted enormous attention since of the application requirements in many fields, such as environment monitoring, satellite clustering, and smart grids. Consensus control is one of the fundamental issues of MASs, and many interesting approaches have been developed [1]–[3]. For instance, the edge-based event-triggered consensus [4], adaptive fuzzy optimal consensus [5], adaptive neural network consensus [6], and so on [7], [8].

Manuscript received Month xx, 2xxx; revised Month xx, xxxx; accepted Month x, xxxx. This work was supported in part by the National Natural Science Foundation of China under Grant 61873112, and the Natural Science Research Project of Higher Education in Jiangsu Province under Grant 18KJB413009. (corresponding author: Jinjun Shan)

Huarong Zhao and Li Peng are with Engineering Research Center of Internet of Things Applications Ministry of Education, Jiangnan University, Wuxi 214122, Jiangsu, China. Huarong Zhao is also with the Department of Earth and Space Science and Engineering, York University, Toronto, ON M3J 1P3, Canada (e-mail: hrzhao@yorku.ca; pengli@jiangnan.edu.cn).

Jinjun Shan is with the Department of Earth and Space Science and Engineering, York University, Toronto, ON M3J 1P3, Canada (e-mail: jjshan@yorku.ca).

Hongnian Yu is with School of Engineering and the Built Environment, Edinburgh Napier University, EH10 5DT Edinburgh, UK (e-mail: H.Yu@napier.ac.uk).

Overall, most results of consensus control methods assume that the relationship among agents is cooperative. However, the competitive and cooperative relationships among agents are coexistence. For example, in a game, the relationship between two team members is collaborative, but the relationship between members on opposite teams is antagonistic. To address this issue, Altafini [9] proposed a bipartite consensus (BC) control approach for MASs with collaborative and antagonistic interactions, where agents are divided into two alliances with opposite objectives. Subsequently, several excellent strategies were developed, such as leader-following BC [10], prescribed performance BC [11], finite-time and fixed-time BC [12]. However, BC is still a topic in its infancy.

Furthermore, the earlier results required explicit or implicit mathematical models, which are called model-based methods. However, using first principles or identification for modeling complex nonlinear MASs is extremely difficult or impossible to obtain accurate dynamics [13]. To bypass the effects of inaccurate dynamics, an alternative method was developed, namely data-driven control, for instants, reinforcement learning [14], [15], Q-learning [16], data-driven iterative learning [17]–[19], adaptive dynamic programming [20], model-free adaptive control (MFAC) [21]–[24]. MFAC is a class of data-driven control for discrete-time nonlinear systems without establishing a neural network, which was first investigated by Hou et al. [25]. Subsequently, Bu et al. extended the results of [25] for MASs to realize consensus tracking control in [26]. Li et al. investigated the time-varying delay for MASs with switching topologies in [27]. A disturbance compensation method was studied by Li et al. [28] and Ren et al. [29] for MASs conducting consensus and formation tasks, respectively. Other interesting works can be found in [30], [31].

The information transmitted among agents is either wired or wireless, where data dropout and measurement noise are inevitable. However, most of the existing data-driven methods are focused on point-to-point MASs, and the networked circumstance of MASs without any communication problems is a strict requirement. Several data-driven results have been developed to address data dropout issues. Bu et al. [32] investigated a data dropout compensation scheme, which was based on the last control input. Combining predictive control and MFAC, data-driven predictive control methods were investigated for a nonlinear signal system by Pang et al. [33], [34]. An input compensation scheme was proposed to mitigate the effects of data dropout in [35]. Chi et al. [36] studied the random data dropout issues for linear and nonlinear repetitive systems and proposed a data-driven iterative learning control method.

The above works only consider the data loss. Although the measurement noise was discussed in [34], [35], how to reduce the noise was not investigated. However, disturbance, especially measurement noise, is often encountered in practical systems, which reduces the control performance and even causes instability of controlled systems. For data-driven control, most of the results were focused on designing an estimator by using pseudo-partial-derivative (PPD) techniques such as [28], [29], [31], and [37]. Although using the PPD technique can reduce the bounded disturbances, the constraints are highly stringent, making the application performance of this method limited. It is noteworthy that the radial basis function neural networks (RBFNNs) is an alternative method for designing an estimator [38]. Due to the simple topologies structure and universal approximation ability, RBFNNs are often employed to model and control nonlinear systems [39]–[44].

In this paper, we combine RBFNNs and the PPD techiniques to develop a new learning-based robust bipartite consensus control (LRBCC) method to address three mainly issues: 1) to reduce the effects of unknown disturbance; 2) to realize bipartite consensus control for heterogeneous nonlinear nonaffine discrete-time MASs with fixed and time-varying switching topologies under antagonistic interactions; 3) to improve BC control performance when MASs are subject to random data dropout in both feedback and forward channels. Although disturbance problems of MASs have been investigated in literature [27] and [28], a disturbance estimator with extreme constraints was designed by using the PPD technique. Although [38] and [40] utilized neural networks to establish disturbance observers, they need an external training process and only function for a single controlled system. Furthermore, the existing compensation methods [32]–[36] for data dropout have good control performance. However, they did not consider how to reduce the unknown disturbances and are hard to be applied for MASs. The designed LRBCC scheme only depends on the input/output data, where information on controlled MASs is no longer needed. It can rapidly discern the unknown disturbance online, and both feedback and forward channels data dropouts are considered.

The remaining sections of this paper are organized as follows: Basic knowledge and problem formulation are introduced in Section II. Section III presents the details of the designed LRBCC algorithm for the MASs with fixed and switching topologies. Several numerical simulations are presented in Section IV. The hardware testing and the summaries are given in Sections V and VI, respectively.

Notations: R, R^{+}, $R^{N\times N}$, Z^{+}, and I stand for the set of real numbers, positive real numbers, $N\times N$ matrices, positive integers, and identity matrices with arbitrary dimension, respectively. $diag(\bullet)$,$sign(\bullet)$, and $round(\bullet)$ denote diagonal matrix, sign function, and rounding function, respectively. $\|\Theta\|$ denotes the Euclidean norm of vector $\Theta \in R^{N}$. Moreover, k=$1,2\ldots$ represent time interval.

II. Preliminary and Problem Formulation

A. Signed Graph Theory

This article employs a signed graph $F = (V, E, A)$ to describe the communication topology of the MASs with N agents, where $V = \{1, 2, \cdots, N\}$, $E = \{(p, j)|p, j \in V\ p \neq j\} \subseteq V \times V$, and $A = [a_{pj}] \in R^{N\times N}$ represent nodes, edges, and the weighted adjacency matrix with elements -1, 0, 1, respectively. Moreover, let $N_p = \{j \in V|(j, p) \in E\}$ denote the neighborhood set of the node p, and $D = diag\{d_1, \cdots, d_N\}$ with $d_p = \sum_{j\in N_p}|a_{pj}|$ denotes the degree matrix of the graph F. In this paper, let node 0 stand for the virtual leader, and an augmentation graph is defined as $\bar{F} = (\bar{V}, \bar{E}, A)$ with $\overline{V} = V \cup \{0\}$ and $\overline{E} = \overline{V} \times \overline{V}$. Then, the Laplacian matrix of $\bar{F}$ can be calculated as $L = -A + D$. The connecting relationship between the virtual leader and agent p is denoted by $B = diag\{b_1, \cdots, b_N\}$. If the leader is directly connected with the agent p that $b_p = 1$. Otherwise, $b_p = 0$.

Generally, the graph $\bar{F}$ is structurally balanced, which includes two opposite groups, V_1 and V_2, and satisfies the three conditions: 1) $V_1 \cup V_2 = V$ and $V_1 \cap V_2 = \emptyset$; 2) If $\forall p, j \in V_z$ with $z \in \{1, 2\}$, $a_{pj} \in \{0, 1\}$; 3) If $\forall p \in V_z$ and $j \in V_q$ with $q \in \{1, 2\}$ and $z \neq q$, $a_{pj} \in \{-1, 0\}$. If $(p, j) \notin E$ or $p = j$, $a_{pj} = 0$. A grouping matrix $s = diag(s_1, \cdots, s_N)$ is usually utilized to represent the relationship between agents and groups, where if agent $p \in V_1$, $s_p = 1$; otherwise, $s_p = -1$. Moreover, A_N is often defined as the set of agents.

B. System Descriptions

A class of SISO (single-input-single-output) nonlinear nonaffine discrete-time MASs with N agents is studied, and the relationship between the input and output of the pth agent satisfies:

$$\begin{aligned} y_p(k+1) \ = \ & f_p(y_p(k), \cdots, y_p(k-n_y), \\ & u_{cp}(k), \cdots, u_{cp}(k-n_u)) + d_p(k) \end{aligned} \tag{1}$$

where n_y, n_u are two unknown positive integers. $u_{cp}(k) \in R$, $y_p(k) \in R$, and $d_p(k) \in R$ stand for the input, output, and unknown bounded disturbance of agent p with $p \in A_N$, respectively. $f_p(\bullet)$ is an unknown nonlinear function, and the communication topology of MASs is expressed by $\bar{F}$.

Two fundamental assumptions of the MFAC framework are presented below.

Assumption 1: The partial derivative of $f_p(\bullet)$ with respect to the control input $u_{cp}(k)$ is continuous.

Assumption 2: Equation (1) satisfies the generalized Lipschitz condition, that is, $|\Delta y_p(k+1)| \leq r|\Delta u_{cp}(k)|$ holds for all k, where $r \in R^{+}$, $\Delta u_{cp}(k) = u_{cp}(k) - u_{cp}(k-1) \neq 0$, and $\Delta y_p(k) = y_p(k) - y_p(k-1)$.

Remark 1: Assumption 1 is a general assumption in the controller design process, and Assumption 2 is a restriction of the controlled systems, which is based on the viewpoint from the engineering applications and energy, implying if the input of the system changes in a bounded range, the corresponding output energy should be also bounded.

Lemma 1 ([21], [28]): If Equation (1) satisfies Assumptions 1 and 2, an virtual linear data model can be obtained as

$$\Delta y_p\left(k+1\right) = \varphi_p\left(k\right)\Delta u_{cp}\left(k\right) + \Delta d_p(k) \tag{2}$$

where $\varphi_p(k)$ with $|\varphi_p(k)| < r$ is called pseudo-partial-derivative (PPD) parameter, and $\Delta d_p(k)$=$d_p(k) - d_p(k-1)$ with $|\Delta d_p(k)| \leq r_d$, that is, the noise $d_p(k)$ is slowly changed.

Assumption 3: For all k, $\varphi_p(k) > \iota > 0$ ($\varphi_p(k) < -\iota < 0$) holds, where $\iota \in R^+$. Here, we assume $\varphi_p(k) > \iota$ which is a general assumption of the existing MFAC methods [25], [26].

Assumption 4 ([45]): If $\bar{F}$ is strongly connected, $L + B$ is an irreducible matrix with positive diagonal elements.

Assumption 5: The components of the controlled MASs are synchronized, and the numbers of successive data dropout are bounded by $\bar{n}$.

Definition 1: The BC error $e_p(k)$ of the agent p with random data dropout and unknown disturbances is defined as

$$e_p(k) = \lim(s_p y_r(k) - y_p(k)) \leq \upsilon, \; p \in A_N \tag{3}$$

where $y_r(k)$ is the output of the virtual leader, and υ is a small bounded constant. s_p is defined in Section II.A.

III. LRBCC Algorithm Design and Convergence Analysis

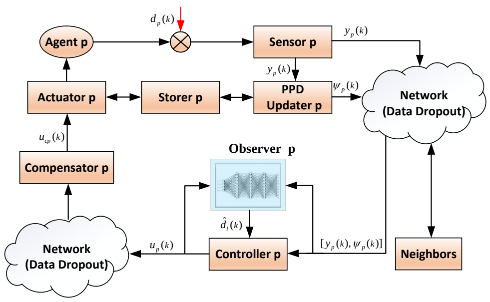


Fig. 1. The diagram of the designed LRBCC method.

Figure 1 presents the diagram of the designed LRBCC method, where if the data dropout does not occur, the controller p and the observer p start to work; otherwise, the compensator p starts to work. When the information of the agent p and its' neighbors is transmitted to the controller p or the commands of the controller p are sent to the agent p, there may exist data dropout caused by a link failure, network jamming, buffer overflow, etc. It is noticed that the desired output $y_r(k)$ of the virtual leader is stored in sorter, which can be obtained by controller p, observer p, and PPD updater p. To address this issue, a compensator is developed and closed to the actuator. In addition, Fig.1 shows that controller p includes a designed radial basis neural network (RBFNN) observer p. The designed RBFNN observer can identify the disturbances online to adjust the output of controller p to reduce the effects of unknown disturbances. Then, the LRBCC method is designed as

$$\begin{aligned} u_{cp}(k) = &\wp_p(k)(u_{cp}(k-1) + \Delta u_{cp}(k^* + n|k^*)) \\ &+ (1 - \wp_p(k))u_p(k) \end{aligned} \tag{4}$$

where $u_p(k)$ and $\Delta u_{cp}(k^*+n|k^*)$ are defined later, and $\wp_p(k)$ is an index function. Whatever the data loss occurs in the feedback or forward channels at time instant k, $\wp_p(k)$=1. Otherwise, $\wp_p(k)$=0.

Remark 2: Although few existing data-driven results [34]–[36] are focused on data dropout for a single system with disturbances, they only consider the feedback channel of the controlled system without considering how to reduce the effects of the unknown disturbances. Moreover, both cooperative and competitive relationships among agents are considered in the proposed LRBCC scheme, which is more general than the traditional consensus methods.

A. Input Gain Compensation Mechanism

To mitigate the effects of data dropout in both the feedback and forward channels, an input gain compensation method is proposed as

$$\Delta u_{cp}(k^* + n|k^*) = \alpha^n \Delta u_{cp}(k^*|k^*) \tag{5}$$

where k^* denotes that the last time instant of the information is transmitted successfully, $n \in Z^+$ represents the number of successive data dropouts, $\alpha \in (0, 1)$ stands for an attenuation factor, and n represents the numbers of successive data dropout. Then, the input signal of the actuator of the agent p is designed as

$$u_{cp}(k) = u_{cp}(k^* + n - 1) + \Delta u_{cp}(k^* + n|k^*) \tag{6}$$

where $k = k^* + n$, and there is an upper bound of n with $\bar{n}$.

B. Disturbance Observer Based on RBFNN

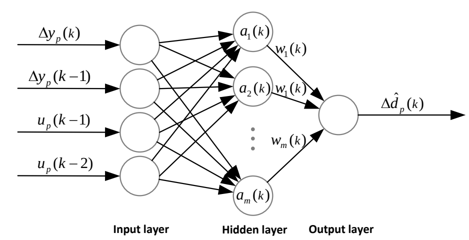


Fig. 2. The diagram of the designed RBFNN disturbance observer.

The disturbance of each agent is estimated by the designed RBFNN observer shown in Fig. 2, where the input vector of RBFNN is $X_p(k)$= $[\Delta y_p(k),\ \Delta y_p(k-1),\ u_p(k-1),\ u_p(k-2)]$, the number of neurons in the hidden layer is m, which is decided by trial and error, with weight vector $W_p(k) = [w_{p1}(k), w_{p2}(k), \cdots, w_{pm}(k)]^T$. Moreover, the radial basis vector is expressed by $A_p(k) = [a_{p1}(k), a_{p2}(k), \cdots, a_{pm}(k)]^T$, and the radial basis function is selected as a Gauss basis function as

$$a_{pi}(k) = \exp(-||X_p(k) - c_{pi}(k)||^2/(2q_{pi}^2(k))), \; i = 1, ..., m$$

where $c_{pi}(k)$ and $q_{pi}(k)$ are the center and width of the ith neuron of the hidden layer, respectively. The cost function is $J_p(k) = (\Delta\tilde{d}_p(k) - \Delta\breve{d}_p)^2/2$, where $\Delta\tilde{d}_p(k) = \tilde{d}_p(k) - \tilde{d}_p(k-1)$ with $\tilde{d}_p(k) = s_p y_r(k) - y_p(k)$. $y_r(k)$ is the output of the virtual leader, which can be obtained from the store. $\tilde{d}_p(k)$ is the real-time disturbance, and $\Delta\breve{d}_p = W_p(k)^T A_p(k)$ is the real-time output of the established RBFNN observer. $\Delta d_p(k)$ is the actual disturbance change rate, and there is an ideal bound ς satisfying

$$\Delta d_p(k) = \Delta\hat{d}_p(k) + \varsigma \tag{7}$$

where $\Delta\hat{d}_p(k) = \hat{W}_p(k)^T A_p(k)$ is the desired output of the RBFNN observer, and $\hat{W}_p(k)$ is the desired weight vector. According to the universal approximation theorem [46], [47], $W_p(k)$ will approximate to $\hat{W}_p(k)$ rapidly, such that $\Delta\breve{d}_p(k) = \Delta\hat{d}_p(k)$. Moreover, the established RBFNN observer is updated by the gradient descent approach as

$$
\begin{aligned}
w_{pi}(k) &= w_{pi}(k-1) + l_p(\Delta\tilde{d}_p - \Delta\breve{d}_p(k))a_{pi}(k) \\
&\quad + a_p(w_{pi}(k-1) - w_{pi}(k-2)) \\
\Delta q_{pi}(k) &= (\Delta\tilde{d}_p(k) - \Delta\breve{d}_p(k))w_{pi}(k)a_{pi}(k) \\
&\quad \times ||X_p(k) - c_{pi}||/q_{pi}^3(k) \\
q_{pi}(k) &= q_{pi}(k-1) + l_p\Delta q_{pi}(k) + a_p\Delta q_{pi}(k-1) \\
\Delta c_{pi}(k) &= (\Delta\tilde{d}_p(k) - \Delta\breve{d}_p(k))w_{pi}(k) \\
&\quad \times (X_{pj}(k) - c_{pij}(k))/q_{pi}^2(k) \\
c_{pij}(k) &= c_{pij}(k-1) + lp\Delta c_{pij}(k) + a_p\Delta c_{pij}(k-1)
\end{aligned}
$$

where l_p and a_p denote the learning rate and the action factor of the establish RBFNN observer, respectively. The similar updating process of RBFNN can be found in [38], [47], [48].

Remark 3: Compared with most existing disturbance compensation schemes requiring that the bounded disturbance is known or periodic change, the change rate of disturbance is bounded in this paper, which is a weak restriction. Compared with other NNs, such as backpropagation (BP) neural networks, RBFNN has a simple structure, can adopt unsupervised learning methods, such as random center and clustering methods, can avoid local optimal solutions, and has a strong ability to approximate any nonlinear function rapidly [38], [47], [48], which guarantees that the designed controller of MASs can identify the disturbance online to relieve the effects of unknown disturbance instantly. Compared with most exciting NNs-based schemes, the proposed LRBCC method is an online learning algorithm, where external training and testing data are no longer needed. Moreover, this paper considers that the real-time disturbance $\tilde{d}_p(k)$ includes measurement noise, external interference, and others. Compared with some offline learning neural networks methods, it is more flexible and has broader application scenarios.

C. Robust BC Algorithm

To realize distributed control, a distributed combined measurement error is designed below.

$$
\begin{aligned}
\zeta_p(k) = \sum_{j\in N_p} |a_{pj}|(sign(a_{pj})y_p(k) - y_j(k)) \\
+ b_p(s_p y_r(k) - y_p(k))
\end{aligned} \tag{8}
$$

where $y_p(k)$ is the output of the sensor p. a_{pj}, b_p, and s_p are defined in Section II.A. The robust BC method is designed as

$$
u_p(k) \begin{cases} u_p(k-1) + \frac{\rho_p\hat{\varphi}_p(k)}{\lambda+\hat{\varphi}_p^2(k)}\zeta_p(k) - \frac{\Delta\breve{d}_p(k)}{\hat{\varphi}_p(k)}, & \Delta\breve{d}_p(k) \le r_d \\ u_p(k-1) + \frac{\rho_p\hat{\varphi}_p(k)}{\lambda+\hat{\varphi}_p^2(k)}\zeta_p(k), & \Delta\breve{d}_p(k) > r_d \end{cases} \tag{9}
$$

where $0 < \rho_p < 1/(d_p + b_p)$, $\lambda > r^2/4(1-\alpha)^2$, $\Delta\breve{d}_p(k)$ is the output of the RBFNN observer defined in Section III.B. If $\Delta\breve{d}_p(k) > r_d$, let $\Delta\breve{d}_p(k) = 0$, where r_d is defined in Lemma 1 and is obtained by trail and error. $\hat{\varphi}_p(k)$ is the estimate of $\varphi_p(k)$, which is defined as

$$
\begin{aligned}
\hat{\varphi}_p(k) =& \frac{-\eta\Delta u_{cp}(k-1)}{u + \Delta u_{cp}^2(k-1)}(\hat{\varphi}_p(k-1)\Delta u_{cp}(k-1)) \\
&+ \frac{\eta\Delta u_{cp}(k-1)}{u + \Delta u_{cp}^2(k-1)}\Delta y_p(k) + \hat{\varphi}_p(k-1)
\end{aligned} \tag{10}
$$

where $0 < \eta < 1$, $u > 0$, $\Delta u_{cp}(k-1) = u_{cp}(k-1) - u_{cp}(k-2)$, and $u_{cp}(k)$ is the input of the actuator p defined in Equation (4). To improve the estimation performance of Equation (10), the following reset laws are adopted.

$$
\begin{aligned}
\hat{\varphi}_p(k) = \hat{\varphi}_p(1),\ if\ |\hat{\varphi}_p(k)| \le \delta\ or\ |\Delta u_{cp}(k-1)| \le \delta \\
or\ sign(\hat{\varphi}_p(k)) \neq sign(\hat{\varphi}_p(1))
\end{aligned} \tag{11}
$$

where $\delta > 0$ is a condition of stop updating for Equation (10), which is often set as 10^{-4} of 10^{-5}. Then, to analyze the convergence of the proposed LRBCC protocol (4), the following Lemma should be presented.

Remark 4: As some exceptions, such as cyber-attacks, physical attacks, and others, cause the output of the established RBFNN unnormal as $\Delta\breve{d}_p(k) \to \infty$, which will destroy the stability of the controlled plant. Moreover, from the previous results [21], [34], [49], it is obtained that if let $\Delta\breve{d}_p(k) = 0$, Equation (9) also can prevent the stability of the controlled system with bounded disturbances, where the results of convergence proof, simulations, and hardware tests can be found in [34], [49]. Hence, the proof of this special situation is omitted.

Lemma 2 ([45]): Let $\Psi(k)$ denote the irreducible substochastic matrix with positive diagonal entries. Then, we have $||\Psi(1)\Psi(2)\cdots\Psi(P)|| < \sigma < 1$, where $P \in Z^+$.

Theorem 1: Considering that the nonlinear MASs (1) with Assumptions 1-5 use the designed input gain compensation method (5) to solve the data dropout issue, employing the established RBFNN observer to estimate the unknown disturbances, and utilizing the designed control law (4) to perform distributed BC control tasks, the BC errors $e_p(k)$ of each agent to track $y_r(k)$ with $\Delta y_r(k) = 0$ or $0 < |\Delta y_r(k)| < r_0$ are ultimately bounded when $k \to \infty$.

Proof: According to the proof of Theorem 2 of [25] and [26], if $0 < \eta < 1$ and $u > 0$, there is a constant $\hat{r} \in R^+$ satisfying $|\hat{\varphi}_p(k)| \le \hat{r}$. Then, the following situations should be analyzed.

Case 1: $\Delta y_r(k) = 0$, that is, the reference is a constant.

Case 1.1: The no data loss case: In this case, $\wp_p(k)$=0, from Equation (4), we have $u_{cp}(k)$=$u_p(k)$. Moreover, from Equations (2), (3), and (9), we have

$$
\begin{aligned}
e_p(k+1) = e_p(k) - \varphi_p(k)\Delta u_{cp}(k) - \Delta d_p(k) \\
\le e_p(k) - \rho_p\vartheta_p(k)\zeta_p(k) + \lambda_1
\end{aligned} \tag{12}
$$

where $\vartheta_p(k) = \varphi_p(k)\hat{\varphi}_p(k)/(\lambda + \hat{\varphi}_p^2(k)) \le r/(2\sqrt{\lambda}) \le 1-\alpha < 1$ since of $\lambda > r^2/4(1-\alpha)^2$, and $\lambda_1 \ge \varphi_p(k)\Delta\breve{d}_p(k)/\hat{\varphi}_p(k) + \Delta d_p(k)$ since $\varphi_p(k)$, $\hat{\varphi}_p(k)$, $\Delta\breve{d}_p(k)$, and $\Delta d_p(k)$ are bounded. Moreover, to facility of the following analysis, we define $e(k) = [e_1(k), e_2(k)\cdots, e_N(k)]^T$, $\zeta(k) =$

$[\zeta_1(k), \zeta_2(k), \cdots, \zeta_N(k)]^T$, $\rho = diag(\rho_1, \rho_2, \cdots, \rho_N)$, and $\vartheta(k) = diag(\vartheta_1(k), \vartheta_2(k), \cdots, \vartheta_N(k))$.

Then, taking norm on both side of the compact of Equation (12), we have

$$\begin{aligned}
&||e(k+1)|| \le ||e(k)|| - ||\rho\vartheta(k)\zeta(k)|| + \lambda_1 \\
&\le ||I - \rho\vartheta(k)(L+B)||||e(k)|| + \lambda_1 \\
&\vdots \\
&\le ||I - \rho\vartheta(k)(L+B)|| \cdots ||I - \rho\vartheta(1)(L+B)||||e(1)|| \\
&\quad + \lambda_1(1 + ||I - \rho\vartheta(k)(L+B)|| + \cdots \\
&\quad + ||I - \rho\vartheta(k)(L+B)|| \cdots ||I - \rho\vartheta(1)(L+B)||) \quad (13)
\end{aligned}$$

Since $0 < \rho_p < 1/(d_p + b_p)$, $0 < \vartheta_p(k) < 1$, and Assumption 4, we can obtain that $I - \rho\vartheta(k)(L+B)$ is an irreducible substochastic matrix with positive diagonal entries. Then, according to Lemma 2 and the similar analysis of Theorems 1 and 3 of [21] and [25], respectively, we can obtain that $\lim_{k\to\infty} ||e(k+1)|| = \lambda_1/(1-\sigma)$.

Case 1.2: The data loss case: In this case, $\wp_p(k)=1$, so that Equation 4 becomes $\Delta u_{cp}(k) = \Delta u_{cp}(k^* + n|k^*)$, where $k = k^* + n$. According to Equation (5), Equation (12) can be rewritten as

$$\begin{aligned}
&e_p(k^*+n+1|k^*) = e_p(k^*+n|k^*) + \Delta d_p(k^*+n|k^*) \\
&\quad - \varphi_p(k^*+n|k^*)\alpha^n \Delta u_{cp}(k^*|k^*) \\
&\le e_p(k^*|k^*) - \psi_p(k^*+n|k^*)\Delta u_{cp}(k^*|k^*) + 2nr_d \qquad (14)\\
&\le e_p(k^*|k^*) - \psi_p(k^*+n|k^*)\Xi_p(k^*|k^*)\rho_p\zeta_p(k^*|k^*) \\
&\quad + \psi_p(k^*+n|k^*)\Delta\breve{d}_p(k^*|k^*)/\hat{\varphi}_p(k^*|k^*) + 2nr_d
\end{aligned}$$

where $\Xi_p(k^*|k^*) = \hat{\varphi}_p(k^*)/(\lambda + \hat{\varphi}_p^2(k^*))$, and $0 < \underline{w} \le \psi(k^* + n|k^*)\Xi_p(k^*|k^*) \le r(1-\alpha^{n+1})/(2(1-\alpha)\sqrt{\lambda}) < 1$ since of $\lambda > r^2/4(1-\alpha)^2$ and $\psi(k^*+n|k^*) = \varphi_p(k^*|k^*) + \varphi_p(k^* + 1|k^*)\alpha^1 + \cdots + \varphi_p(k^*+n|k^*)\alpha^n \le r(1-\alpha^{n+1})/(1-\alpha)$. Thus, Equation (14) becomes

$$e_p(k^*+n+1|k^*) = e_p(k^*|k^*) - \underline{w}\rho_p\zeta_p(k^*|k^*) + \lambda_2 \quad (15)$$

where $\lambda_2 \ge \psi_p(k^*+n|k^*)\Delta\breve{d}_p(k^*|k^*)/\hat{\varphi}_p(k^*|k^*) + 2nr_d$.

Taking norm on both sides of the compact of Equation (15), the following inequality can be obtained.

$$\begin{aligned}
&||e(k^*+n+1|k^*)|| = ||e(k^*|k^*)|| - \underline{w}||\rho\zeta(k^*|k^*)|| + \lambda_2 \\
&\le ||I - \underline{w}\rho(L+B)||||e(k^*|k^*)|| + \lambda_2 \qquad (16)
\end{aligned}$$

Since $0 < \underline{w} < 1$, we can also obtain that $I - \underline{w}\rho(L+B)$ is an irreducible substochastic matrix with positive diagonal entries. Thus, we have $\lim_{k\to\infty} ||e(k^*+n+1|k^*)|| = \sigma\lambda_1/(1-\sigma) + \lambda_2$.

Case 2: $0 < |\Delta y_r(k)| < r_0$, that is, the reference is time-varying and bounded by r_0. Thus, Equations (13) and (16) become

$$||e(k+1)|| \le ||I - \rho\vartheta(k)(L+B)||||e(k)|| + \lambda_3 \quad (17)$$

and

$$\begin{aligned}
&||e(k^*+n+1|k^*)|| \\
&\qquad \le ||I - \underline{w}\rho(L+B)||||e(k^*|k^*)|| + \lambda_4 \qquad (18)
\end{aligned}$$

where $\lambda_3 \ge \lambda_1 + r_0$, $\lambda_4 \ge \lambda_2 + 2nr_0$, and $n < \bar{n}$. According to the similar analysis process of Case 1, we obtain that the tracking errors are ultimately bounded by $\lim_{k\to\infty} ||e(k+1)|| = \lambda_3/(1-\sigma)$ in the no data loss case and $\lim_{k\to\infty} ||e(k^*+n+1|k^*)|| = \sigma\lambda_3/(1-\sigma) + \lambda_4$ in the data loss case.

Overall, the designed LRBCC algorithm can guarantee that the bipartite consensus errors of the MASs with random data dropout and unknown disturbance are declined to a small range around the origin. ■

Remark 5: Roughly speaking, the upper bound $\bar{n}$ of data dropouts and references' change rate r_0 are not too big. If $\bar{n}$ tends to infinity, we should exchange the controlled devices. Moreover, the references are slowly changing or unchanging in most control tasks, such as driving trains, cruises, and aircraft. Hence, the designed scheme is valuable to engineering application.

D. Extension to Switching Topologies

In this study, the time-varying switching topologies issue of MASs is considered. To facility of describing the time-varying switching topologies, all of the possible topologies are represented by the graph $\bar{F}^i(k)$, $i = 1, 2, \ldots, \chi$, $\chi \in Z^+$. The corresponding Laplacian matrices, connecting matrices, degree matrices, grouping matrices, and adjacency matrices are defined as $L^i(k)$, $B^i(k) = diag\{b_1^i(k), \cdots, b_N^i(k)\}$, $D^i(k) = diag\{d_1^i(k), \cdots, d_N^i(k)\}$, $s^i(k) = diag(s_1^i(k), \cdots, s_N^i(k))$, and $A^i(k) = [a_{pj}^i(k)] \in R^{N\times N}$, respectively.

Assumption 6 ([45]): Suppose that $\bar{F}^i(k)$ is strongly connected, that is, $L^i(k) + B^i(k)$ is an irreducible matrix with positive diagonal elements.

The distributed combined measurement error (8) becomes

$$\begin{aligned}
\zeta_p(k) = &\sum_{j\in N_p} |a_{pj}^i(k)|(sign(a_{pj}^i(k))y_p(k) - y_j(k)) \\
&+ b_p^i(k)(s_p^i(k)y_r(k) - y_p(k))
\end{aligned} \quad (19)$$

and the distributed BC control method (9) is modified as

$$u_p(k) \begin{cases} u_p(k-1) + \frac{\rho_p^i\hat{\varphi}_p(k)}{\lambda + \hat{\varphi}_p^2(k)}\zeta_p(k) - \frac{\Delta\breve{d}_p(k)}{\hat{\varphi}_p(k)}, & \Delta\breve{d}_p(k) \le r_d \\ u_p(k-1) + \frac{\rho_p^i\hat{\varphi}_p(k)}{\lambda + \hat{\varphi}_p^2(k)}\zeta_p(k), & \Delta\breve{d}_p(k) > r_d \end{cases} \quad (20)$$

where $0 < \rho_p^i < 1/(d_p^i + b_p^i)$, $\lambda > r^2/4(1-\alpha)^2$, $\Delta\breve{d}_p(k)$ is the output of the RBFNN observer defined in Section III.B.

Theorem 2: Considering that MASs (1) are restrained by Assumptions 1-3, 5, and 6, applying the designed input gain compensation method (5), the established RBFNN observer, the PPD estimation laws (10) and (11), and the designed control law (20) to implement BC tasks, the BC errors of the MASs with time-varying switching topologies are bounded.

Proof: **Case 1:** $\Delta y_r(k) = 0$. According to Equation (19), Equations (13) and (16) can be rewritten as

$$||e(k+1)|| \le ||I - \rho^i\vartheta(k)(L^i(k) + B^i(k))||||e(k)|| + \lambda_1 \quad (21)$$

and

$$||e(k^*+n+1|k^*)|| \leq ||I - \underline{w}\rho^i(L^i(k)+B^i(k))|| \times ||e(k^*|k^*)|| + \bar{\lambda}_2 \quad (22)$$

where $\rho^i = diag(\rho_1^i, \cdots, \rho_N^i)$. Then, according to Assumption 6 and $0 < \rho_p^i < 1/(d_p^i + b_p^i)$, we obtain that $I - \rho^i\vartheta(k)(L^i(k)+B^i(k))$ and $I - \underline{w}\rho^i(L^i(k)+B^i(k))$ are irreducible substochastic matrices with positive diagonal entries.

Case 2: $0 < |\Delta y_r(k)| < r_0$. From Equations (17) and (18), we also can obtain similar Equations as (21) and (22).

Thus, according to the analysis of Theorem 1, we can also obtain that $e_p(k)$ is bounded. ■

Remark 6: From Theorems 1 and 2, it is found that the boundedness of the tracking error is directly affected by parameters ρ_p^i and $\bar{\lambda}_1$. From Equation (13), it is found that if ρ_p^i is close to lower bound 0, the error will future cut down. However, if ρ_p^i is close to upper bound $1/(d_p^i + b_p^i)$, convergence rate will be improved. Moreover, increasing the value of λ aways can improve the stability of controlled systems, but it will slow down the convergence rate. Similar results also can be found in [21], [27].

IV. Numerical Simulations

In this section, we have employed four simulation examples to demonstrate the correctness and effectiveness of the proposed LRBCC scheme for the MASs with data dropout and unknown disturbances. All possible topologies of the MASs in the examples are presented in Fig. 3, where five agents split into two teams, V_1 and V_2. Moreover, the direction of information transmission is only along the direction of the arrow, and the red and black arrows are represented the antagonistic and collaborative interactions between connected agents, respectively.

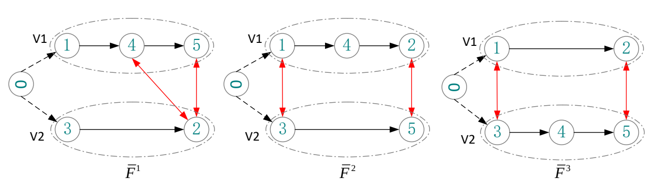


Fig. 3. The communication topologies of MASs.

A. MASs with Fixed Topology

For the simulation Examples 1 to 3, we select the topology $\bar{F}^1$ as shown in Fig. 3 for five heterogeneous agents with

$$
\begin{aligned}
y_1(k+1) &= y_1(k)u_1(k)/(1+y_1^2(k)) + u_1(k)+d_1(k)\\
y_2(k+1) &= y_2(k)u_2^2(k)/(1+y_2^2(k)) + u_2(k)+d_2(k)\\
y_3(k+1) &= y_3(k)/(1+y_3^2(k)+u_3(k)) + u_3(k)+d_3(k)\\
y_4(k+1) &= y_4(k)u_4^3(k)/(1+y_4^2(k)+u_4(k))\\
&\quad + u_4(k)+d_4(k)\\
y_5(k+1) &= y_5^2(k)u_5^3(k)/(1+y_5^3(k)+u_5^2(k))\\
&\quad + u_5^2(k)/(1+y_5^2(k)) + d_5(k)
\end{aligned}
$$

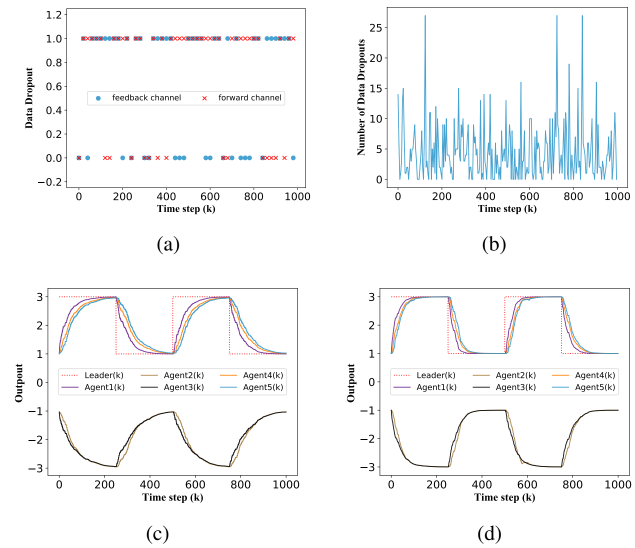


Fig. 4. Bipartite consensus control for the MASs without disturbance in Example 1: (a) Random data loss; (b) The numbers of consecutive data losses; (c) Without input compensation; (d) With input compensation.

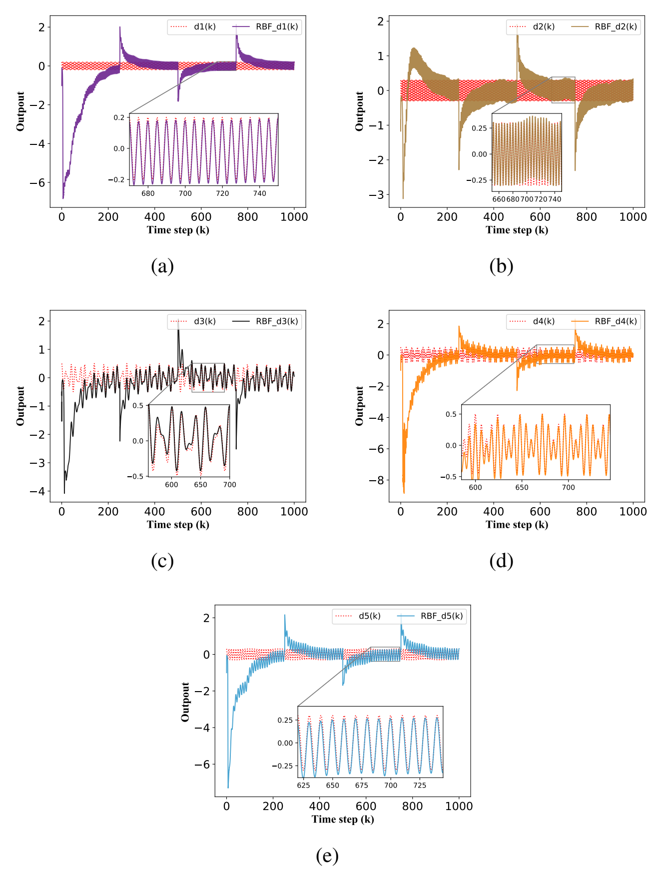
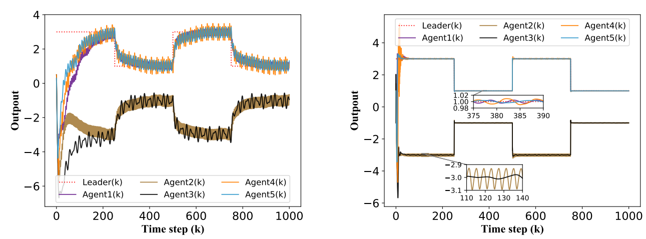


Fig. 5. Performances of the designed online learning RBFNN disturbance observers in Example 2: (a), (b), (c), (d), and (e) are disturbances estimation of five agents, repetitively.

where $d_p(k)$ are the unknown disturbance, and the output of virtual leader is desired as $y_r(k) = 2 + (-1)^{round(k/250)}$. Firstly, we assume $d_p(k)=0$ and initial conditions are set as $\rho_p = 0.32$ with $p = 1,2,3,4,5$, $\lambda=45$, $\alpha=0.8$,

$y_1(k)$=$y_4(k)$=$y_5(k)$=1, and $y_2(k)$=$y_3(k)$= -1 to verify the effectiveness of the developed input compensation method shown in Fig. 4, where the input compensation scheme effectively reduces the effects of data dropouts and protect the stability of the controlled MASs performing bipartite consensus tasks.

Furthermore, to discuss the effectiveness of the RBFNN observers for the disturbances, we set $d_1(k)$= $0.2sin(k\Omega/50)$, $d_2(k)$= $0.3sin(k\Omega/40)$, $d_3(k)$= $0.2cos(k\Omega/70)$ + $0.3sin(k\Omega/100)$, $d_4(k)$= $0.3cos(k\Omega/30)$ + $0.2sin(k\Omega/40)$, and $d_5(k)$= $0.3sin(k\Omega/50)$. Moreover, the parameters of the established RBFNN are discussed in Section III.B, where the number of neurous in the hidden layer is m = 7, learning rate is l_p = 0.12, action factor is a_p = 0.05, and all initial conditions are set as 0.1. The other parameters are set the same as in Example 1. Then, the corresponding results are shown in Figs. 5 and 6.

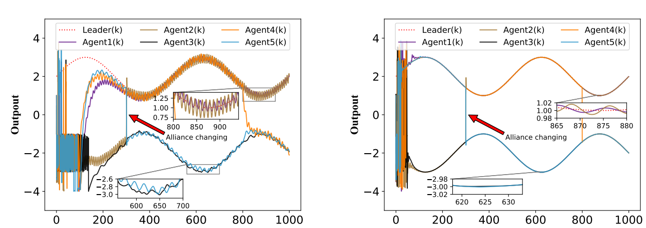


(a) (b)

Fig. 6. Bipartite consensus control performances of the MASs with unknown disturbances in Example 3: (a) Without the RBFNN disturbance observer; (b) With the RBFNN disturbance observer.

Fig. 5 shows that the designed LRBCC with the designed RBFNN disturbance observers can rapidly estimate the disturbances of the corresponding agents. Compared with Figs. 4.d and 6.b, we can see that the designed RBFNN disturbance observer also can improve the convergence rate.

B. MASs with Switching Topologies



(a) (b)

Fig. 7. Bipartite consensus performances of the MASs with time-varying trajectory and switching topologies in Example 4: (a) The existing method [34]; (b) The designed LRBCC method.

To verify that the designed LRBCC scheme is also fitting the switching topologies of MASs tracking time-varying trajectory, the simulation results are shown in Fig. 7, where we assume that the time-varying topologies shown in Fig.3 are governed by $\bar{F}^i$=$\bar{F}^1$, $0 < k \leq 300$; $\bar{F}^i$=$\bar{F}^2$, $300 < k \leq 800$; $\bar{F}^i$=$\bar{F}^3$, $800 < k \leq 1000$. Moreover, the output of the virtual leader is time-varying as y_r = $sin(\pi/300)$. The data loss signal and external noises are set the same as in Example 1. From Fig. 3, it is found that the upper bound of ρ_p is about 0.33. Hence, the parameters of this simulation can also be set the same with Example 1.

From Fig. 7, even if the alliances of agents 2, 4, and 5 are changed, the designed RBFNN method also predicts each agent's unknown noise rapidly and governs MASs to perform the bipartite consensus time-varying tracking task, which illustrates the effectiveness of Theorem 2. Moreover, compared with Figs. 7.a and 7.b, the designed RBFNN scheme has better performance than the existing algorithm in [34] to reduce the effects of the unknown disturbances.

V. Hardware Experiment

In this hardware testing, the controlled MASs consist of five SRV02 units with different components, five amplifiers, and three Q2-USB data acquisitions shown in Fig. 8, designed by Quanser. We use the same topology and parameters as used in Example 1 to verify the practicality of the designed LRBCC method for five SRV02 units against data dropout and the unknown disturbance, including measurement noise and the added disturbances, where data loss signal and the added disturbances are set the same as in Example 1. Moreover, the sample time is 0.002s, and the total running time is 10s, where the outpout of the virtual leader is set as $y_r(k)$= $2 + (-1)^{round((k+1250)/1250)}$.

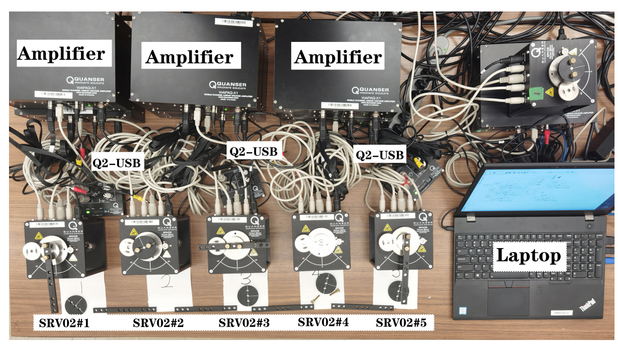
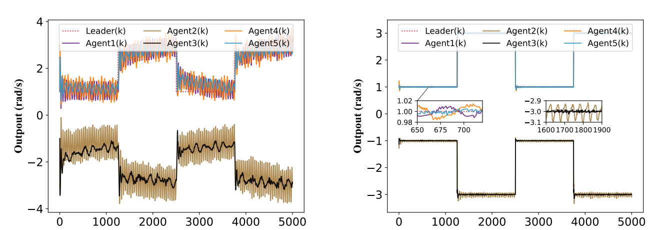


Fig. 8. The experimental system with five heterogeneous SRV02.



(a) (b)

Fig. 9. Performances of bipartite consensus with five SRV02 in Example 5: (a) The designed LRBCC method without the RBFNN disturbance observer; (b) The designed LRBCC method with the RBFNN disturbance observer.

Compared with Figs. 9.a and 9.b, we can find that the RBFNN disturbance observer can rapidly mitigate the effects of unknown disturbances. Furthermore, it is noted that the performances of Figs. 6.b and 9.b are similar, and the designed LRBCC scheme can be directly applied to different systems, where the neural networks can quickly estimate noises and reduce the effects of the noises without any prior training processes.

VI. Conclusions

An data-driven learning-based robust bipartite consensus control method has been proposed for unknown nonlinear nonaffine heterogeneous discrete-time multiagent systems with data dropout and unknown disturbance. The convergence of the designed scheme is strictly demonstrated, where sufficient conditions have been derived. Moreover, the collaborative and antagonistic relationships among agents have been considered. Meanwhile, the designed method has been extended to time-varying switching topologies and has been verified by simulation and hardware testing. In our future efforts, we will extend the developed method for controlling multi-input and multi-output systems.

References

[1] L. Ma, Z. Wang, Q. Han, and Y. Liu, "Consensus control of stochastic multi-agent systems: a survey," *Science China Information Sciences*, vol. 60, no. 12, pp. 1–15, 2017.

[2] Y. Li and C. Tan, "A survey of the consensus for multi-agent systems," *Systems Science & Control Engineering*, vol. 7, no. 1, pp. 468–482, 2019.

[3] D. Zhang, G. Feng, Y. Shi, and D. Srinivasan, "Physical safety and cyber security analysis of multi-agent systems: A survey of recent advances," *IEEE/CAA Journal of Automatica Sinica*, vol. 8, no. 2, pp. 319–333, 2021.

[4] H. Zhao, X. Meng, and S. Wu, "Distributed edge-based event-triggered coordination control for multi-agent systems," *Automatica*, vol. 132, p. 109797, 2021.

[5] K. Li and Y. Li, "Fuzzy adaptive optimal consensus fault-tolerant control for stochastic nonlinear multi-agent systems," *IEEE Transactions on Fuzzy Systems*, DOI 10.1109/TFUZZ.2021.3094716, 2021.

[6] X. Jin, S. Lü, and J. Yu, "Adaptive nn-based consensus for a class of nonlinear multiagent systems with actuator faults and faulty networks," *IEEE Transactions on Neural Networks and Learning Systems*, 2021.

[7] J. Xu, Y. Niu, and Y. Zou, "Finite-time consensus for singularity-perturbed multiagent system via memory output sliding-mode control," *IEEE Transactions on Cybernetics*, DOI 10.1109/TCYB.2021.3051366, 2021.

[8] L. Ding, Q. Han, X. Ge, and X. Zhang, "An overview of recent advances in event-triggered consensus of multiagent systems," *IEEE transactions on cybernetics*, vol. 48, no. 4, pp. 1110–1123, 2017.

[9] C. Altafini, "Consensus problems on networks with antagonistic interactions," *IEEE transactions on automatic control*, vol. 58, no. 4, pp. 935–946, 2012.

[10] G. Zhao and C. Hua, "Leaderless and leader-following bipartite consensus of multiagent systems with sampled and delayed information," *IEEE Transactions on Neural Networks and Learning Systems*, DOI 10.1109/TNNLS.2021.3106015, 2021.

[11] A. K. Gkesoulis and H. E. Psillakis, "Prescribed performance bipartite consensus for nonlinear agents with antagonistic interactions: A pi transformation approach," *Journal of the Franklin Institute*, vol. 358, no. 4, pp. 2382–2404, 2021.

[12] T. Han, Z. Guan, B. Xiao, and H. Yan, "Bipartite average tracking for multi-agent systems with disturbances: Finite-time and fixed-time convergence," *IEEE Transactions on Circuits and Systems I: Regular Papers*, DOI 10.1109/TCSI.2021.3104933, 2021.

[13] S. Xiong and Z. Hou, "Data-driven formation control for unknown mimo nonlinear discrete-time multi-agent systems with sensor fault," *IEEE Transactions on Neural Networks and Learning Systems*, DOI 10.1109/TNNLS.2021.3087481, 2021.

[14] H. Zhang, H. Jiang, Y. Luo, and G. Xiao, "Data-driven optimal consensus control for discrete-time multi-agent systems with unknown dynamics using reinforcement learning method," *IEEE Transactions on Industrial Electronics*, vol. 64, no. 5, pp. 4091–4100, 2016.

[15] T. T. Nguyen, N. D. Nguyen, and S. Nahavandi, "Deep reinforcement learning for multiagent systems: A review of challenges, solutions, and applications," *IEEE transactions on cybernetics*, vol. 50, no. 9, pp. 3826–3839, 2020.

[16] W. Chiu, C. Hu, and K. Chiu, "Renewable energy bidding strategies using multiagent q-learning in double-sided auctions," *IEEE Systems Journal*, DOI 10.1109/JSYST.2021.3059000, 2021.

[17] X. Yu, Z. Hou, and M. M. Polycarpou, "Distributed data-driven iterative learning consensus tracking for nonlinear discrete-time multi-agent systems," *IEEE Transactions on Automatic Control*, DOI 10.1109/TAC.2021.3105653, 2021.

[18] J. Feng, W. Song, H. Zhang, and W. Wang, "Data-driven robust iterative learning consensus tracking control for mimo multiagent systems under fixed and iteration-switching topologies," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, DOI 10.1109/TSMC.2020.3017289, 2020.

[19] H. Zhao, L. Peng, and H. Yu, "Quantized model-free adaptive iterative learning bipartite consensus tracking for unknown nonlinear multi-agent systems," *Applied Mathematics and Computation*, vol. 412, p. 126582, 2022.

[20] H. Zhang, H. Ren, Y. Mu, and J. Han, "Optimal consensus control design for multiagent systems with multiple time delay using adaptive dynamic programming," *IEEE Transactions on Cybernetics*, DOI 10.1109/TCYB.2021.3090067, 2021.

[21] H. Zhao, L. Peng, and H. Yu, "Model-free adaptive consensus tracking control for unknown nonlinear multi-agent systems with sensor saturation," *International Journal of Robust and Nonlinear Control*, vol. 31, no. 13, pp. 6473–6491, 2021.

[22] R. Chi, Y. Hui, S. Zhang, B. Huang, and Z. Hou, "Discrete-time extended state observer-based model-free adaptive control via local dynamic linearization," *IEEE Transactions on Industrial Electronics*, vol. 67, no. 10, pp. 8691–8701, 2019.

[23] W. Song, J. Feng, and S. Sun, "Data-based output tracking formation control for heterogeneous mimo multiagent systems under switching topologies," *Neurocomputing*, vol. 422, pp. 322–331, 2021.

[24] Z. Hou, R. Chi, and H. Gao, "An overview of dynamic-linearization-based data-driven control and applications," *IEEE Transactions on Industrial Electronics*, vol. 64, no. 5, pp. 4076–4090, 2016.

[25] Z. Hou and S. Jin, "A novel data-driven control approach for a class of discrete-time nonlinear systems," *IEEE Transactions on Control Systems Technology*, vol. 19, no. 6, pp. 1549–1558, 2010.

[26] X. Bu, Z. Hou, and H. Zhang, "Data-driven multiagent systems consensus tracking using model free adaptive control," *IEEE transactions on neural networks and learning systems*, vol. 29, no. 5, pp. 1514–1524, 2017.

[27] C. Li and G. Liu, "Data-driven consensus for non-linear networked multi-agent systems with switching topology and time-varying delays," *Iet Control Theory & Applications*, vol. 12, no. 12, pp. 1773–1779, 2018.

[28] H. Li, Y. Wang, and M. Pang, "Disturbance compensation based model-free adaptive tracking control for nonlinear systems with unknown disturbance," *Asian Journal of Control*, vol. 23, no. 2, pp. 708–717, 2021.

[29] Y. Ren and Z. Hou, "Robust model-free adaptive iterative learning formation for unknown heterogeneous non-linear multi-agent systems," *IET Control Theory & Applications*, vol. 14, no. 4, pp. 654–663, 2020.

[30] J. Zhang, S. Chai, B. Zhang, and G. Liu, "Distributed data-driven tracking control for networked nonlinear mimo multi-agent systems subject to communication delays," *Neurocomputing*, DOI 10.1016/j.neucom.2019.12.075, 2019.

[31] J. Feng, W. Song, H. Zhang, and W. Wang, "Data-driven robust iterative learning consensus tracking control for mimo multiagent systems under fixed and iteration-switching topologies," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, DOI 10.1109/TSMC.2020.3017289, 2020.

[32] X. Bu, F. Yu, Z. Hou, and H. Zhang, "Model-free adaptive control algorithm with data dropout compensation," *Mathematical Problems in Engineering*, vol. 2012, DOI 10.1155/2012/329186, 2012.

[33] Z. Pang, G. Liu, D. Zhou, and D. Sun, "Data-based predictive control for networked nonlinear systems with network-induced delay and packet dropout," *IEEE Transactions on Industrial Electronics*, vol. 63, no. 2, pp. 1249–1257, 2015.

[34] Z. Pang, G. Liu, D. Zhou, and D. Sun, "Data-based predictive control for networked nonlinear systems with packet dropout and measurement

noise," *Journal of Systems Science and Complexity*, vol. 30, no. 5, pp. 1072–1083, 2017.

[35] Z. Pang, G. Liu, D. Zhou, and D. Sun, "Data-driven control with input design-based data dropout compensation for networked nonlinear systems," *IEEE Transactions on Control Systems Technology*, vol. 25, no. 2, pp. 628–636, 2016.

[36] R. Chi, Y. Lv, and Z. Hou, "Compensation-based data-driven ilc with input and output package dropouts," *International Journal of Robust and Nonlinear Control*, vol. 30, no. 3, pp. 950–965, 2020.

[37] Y. Wang, H. Li, X. Qiu, and X. Xie, "Consensus tracking for nonlinear multi-agent systems with unknown disturbance by using model free adaptive iterative learning control," *Applied Mathematics and Computation*, vol. 365, p. 124701, 2020.

[38] Q. Yu, Z. Hou, X. Bu, and Q. Yu, "Rbfnn-based data-driven predictive iterative learning control for nonaffine nonlinear systems," *IEEE transactions on neural networks and learning systems*, vol. 31, no. 4, pp. 1170–1182, 2019.

[39] Z. Chen, F. Huang, W. Chen, J. Zhang, W. Sun, J. Chen, J. Gu, and S. Zhu, "Rbfnn-based adaptive sliding mode control design for delayed nonlinear multilateral telerobotic system with cooperative manipulation," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 2, pp. 1236–1247, 2019.

[40] B. Xuhui, H. Zhongsheng, Y. Fashan, and F. Ziyi, "Model free adaptive control with disturbance observer," *Journal of Control Engineering and Applied Informatics*, vol. 14, no. 4, pp. 42–49, 2012.

[41] Z. Wang, L. Liu, and H. Zhang, "Neural network-based model-free adaptive fault-tolerant control for discrete-time nonlinear systems with sensor fault," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 47, no. 8, pp. 2351–2362, 2017.

[42] D. Liu and G. Yang, "Neural network-based event-triggered mfac for nonlinear discrete-time processes," *Neurocomputing*, vol. 272, pp. 356–364, 2018.

[43] L. Liu, Y. Liu, and S. Tong, "Neural networks-based adaptive finite-time fault-tolerant control for a class of strict-feedback switched nonlinear systems," *IEEE transactions on cybernetics*, vol. 49, no. 7, pp. 2536–2545, 2018.

[44] X. Yang, X. Zheng, and H. Gao, "Sgd-based adaptive nn control design for uncertain nonlinear systems," *IEEE transactions on neural networks and learning systems*, vol. 29, no. 10, pp. 5071–5083, 2018.

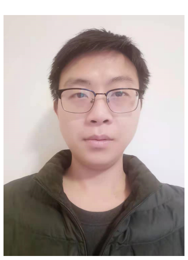
[45] S. Yang, J. Xu, and X. Li, "Iterative learning control with input sharing for multi-agent consensus tracking," *Systems & Control Letters*, vol. 94, pp. 97–106, 2016.

[46] X. Zheng and X. Yang, "Command filter and universal approximator based backstepping control design for strict-feedback nonlinear systems with uncertainty," *IEEE Transactions on Automatic Control*, vol. 65, no. 3, pp. 1310–1317, 2019.

[47] J. Park and I. W. Sandberg, "Universal approximation using radial-basis-function networks," *Neural computation*, vol. 3, no. 2, pp. 246–257, 1991.

[48] J. Moody and C. Darken, *Learning with localized receptive fields*. Yale Univ., Department of Computer Science, 1988.

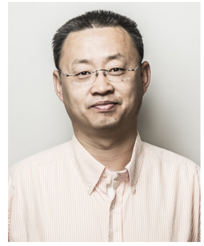
[49] H. Zhao, L. Peng, P. Wu, and H. Yu, "A novel bipartite consensus tracking scheme for unknown nonlinear multi-agent systems: Theoretical analysis and applications," *Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering*, DOI 10.1177/09596518211060976, 2021.



Huarong Zhao received the M.S. degree in mechatronic engineering from Guilin University of Electronic Technology, Guilin, China, in 2018.

He is currently working toward the Ph.D. degree at the School of Internet of Things Engineering in Jiangnan University, Wuxi, China and is an international visiting research trainee of the Department of Earth and Space Science and Engineering, York University, Toronto ON, Canada.

His research interests include multi-agent systems coordination control, data-driven control, and intelligent control.



jinjun Shan (SM'08) received the Ph.D. degree in spacecraft design from the Harbin Institute of Technology, Harbin, China, in 2002.

He is currently a Full Professor of Space Engineering and Chair of the Department of Earth and Space Science and Engineering, York University, Toronto, ON, Canada. Prior to his appointment at York, he was a Postdoctoral Fellow with the University of Toronto Institute for Aerospace Studies. His research interests include dynamics, control, and navigation.

Dr. Shan was the recipient of the Alexander von Humboldt Research Fellowship and JSPS Invitation Fellowship in 2012. Since 2007, he has been a Professional Engineer in Ontario.

Li Peng received the Ph.D. degree from the School of Information Engineering, University of Science and Technology, Beijing, in 2002. He is currently a Professor at the School of Internet of Things Engineering, Jiangnan University, Wuxi, China. He is a member of the Chinese Computer Association, and also Chinese Artificial Intelligent Association. His research interests are computer simulation, intelligent control and visual wireless sensor network.

Hongnian Yu is the Smart Technology Research Centre Director the Head of Research with the School of Engineering and the Built Environment, Edinburgh Napier University. His research covers the two main areas: 1) robotics with applications in the rescue and recovery operations, and healthcare and 2) ICT enabled healthcare including assistive technologies in supporting elderly and people with dementia, and activity recognition of elderly people. He has published over 200 journal and conference research papers.

He is a member of the EPSRC-Peer Review College and a Fellow of IET and RSA. He has held several research grants worth about ten million pounds from the U.K., EPSRC, the Royal Society, and the European, as well as from industry. He was awarded the F.C. William Premium for his paper on adaptive and robust control of robot manipulators by the IEE Council, and has won the Gold Medal on The World Exhibition on Inventions, Research, and New Technologies, INNOVA 2009, Brussels, the International Exhibition of Inventions, Geneva, Switzerland, in 2010, for the invention "Method and device for driving mobile inertial robots"; and the 43rd International Exhibition of Inventions, New Techniques, and Products, Geneva, in 2015.