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Data-based bipartite formation control for multi-agent systems with communication constraints

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Abstract

This article investigates data-driven distributed bipartite formation issues for discrete-time multi-agent systems with communication constraints. We propose a quantized data-driven distributed bipartite formation control approach based on the plant's quantized and saturated information. Moreover, compared with existing results, we consider both the fixed and switching topologies of multi-agent systems with the cooperative-competitive interactions. We establish a time-varying linear data model for each agent by utilizing the dynamic linearization method. Then, using the incomplete input and output data of each agent and its neighbors, we construct the proposed quantized data-driven distributed bipartite formation control scheme without employing any dynamics information of multi-agent systems. We strictly prove the convergence of the proposed algorithm, where the proposed approach can ensure that the bipartite formation tracking errors converge to the origin, even though the communication topology of multi-agent systems is time-varying switching. Finally, simulation and hardware tests demonstrate the effectiveness of the proposed scheme.

Keywords

Data-driven control, multi-agent systems, bipartite formation, data quantization, sensor saturation

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Introduction

In nature, many creatures work together to accomplish a complicated and amazing task. For instance, birds keep a "V" formation to migrate, and ants preserve a separation distance to bring food. Enlightened by this observation, formation control of multi-agent systems (MASs) has attracted increasing attention with wide applications, such as unmanned aerial vehicles,[1] satellite formation,[2] and electrical power grids.[3] An essential issue on the formation of MASs is how to design an appropriate control protocol such that the states/outputs of all agents can achieve and maintain a desired geometric pattern. To solve this issue for MASs, distributed control[4–7] is one of the effective approaches.

Recently, numerous distributed control results[8–14] for MASs have been published. For example, Wang et al.[8] proposed a robust time-varying formation control protocol for the second-order MASs, Shi et al.[9] studied an adaptive event-triggered triggered formation control method for heterogeneous MASs, a dynamic event-triggered formation control scheme was proposed by Ge et al.,[10] Pan et al.[11] investigated a multiaplyer graph and design a model predictive formation control method, the finite-time formation control for linear MASs was studied by Duan et al.,[12] and some related research topics on formation control problems were surveyed.[13,14] However, to the best of our knowledge, the robust formation control problem for MASs is still open to be investigated.

The above-distributed formation control schemes require the controlled plant's accurate mathematical model called model-based control (MBC) algorithms. However, plant modeling employing the first identification principles becomes extremely difficult because the practical industrial process becomes more complex and integrated.[15] Besides, it is expensive to build a dynamics model for each agent. Furthermore, the error between a practical plant and a mathematical model is inevitable, which may deteriorate systems' stability. Hence, a data-driven control (DDC) approach becomes an alternative way to formulate a robust control protocol for complex systems, for instance, model-free adaptive control (MFAC),[15–20] model-free adaptive iterative learning control (MFAILC),[21–23] virtual reference feedback tuning (VRFT),[24] iterative feedback tuning (IFT),[25] proportional-integral-derivative (PID),[26] reinforcement learning (RL)[27–30], and so on.[31–33] It is noted that MFAILC is an effective approach for the nonlinear system to conduct repeatable tasks. The VRFT, IFT, PID, and RL have good control performances to govern nonlinear systems with nonrepetitive missions. However, they have some implementation difficulties, such as many parameters to be adjusted, the Actor-Critic networks to be estimated, and training-testing data to be prepared.

MFAC is an attractive DDC framework[34] for discrete-time nonlinear systems with unknown dynamics by only employing measurable input/output (I/O) data. The main idea of the MFAC is to apply dynamic linearization technology to establish a series of the equivalent linear data model for the controlled systems. Since MFAC was studied by Hou et al.,[17] many related approaches have been developed, including single system and multi-systems. Especially, for single system, numerous issues have been investigated, such as measurement disturbance,[26] data dropout,[35] cyber attack,[36] and data quantization.[37] As MASs, an effective consensus tracking control scheme was formulated by Bu et al.[38] The switching topologies and time-varying delays of MASs were considered by Li et al.[15] The disturbance and heterogeneous problems of MASs to achieve formation control were studied by Xiong et al.[39]

In the aforementioned related DDC formation approaches, saturation nonlinearity and data quantization have rarely been considered while designing the controller. Although data quantization[37] was studied, it only considered single system. The consensus problem of MASs with output saturation[40] was investigated, but it was dependent on terminal iterative learning and only was suitable for MASs under repeatable operations. In the DDC field, especially using the MFAC concept, few results have been developed for MASs conducting formation control with sensor saturation and data quantization to the best of our knowledge. This is the first motivation for this paper.

On the other hand, in a practical industrial process, sensor saturation and data quantization are important issues. Firstly, the measurement range of the sensor is not unlimited, which is constrained by the hardware, so the sensor saturation is inevitable. Secondly, during the information transmitting process, signals of agents have to be quantized into a finite number, which is necessary for reducing the transmission burden because of the communication networks with limited bandwidth. Moreover, both sensor saturation and data quantization are hot topics of the MBC field. For example, Lin et al.[41] proposed an event-triggering consensus control scheme for MASs with quantized state information and delays. Both the quantization and saturation problems for MASs were investigated by Chen et al.[42] The prescribed performance and input quantization issues were discussed by Liang et al.[43] Quantization and attack problems were investigated by Huang et al.[44] Further details for solving quantization and saturation problems can be found in the survey papers.[45,46]

It is noted that most existing approaches[38–46] for MASs only consider the collaborative interactions among agents. In fact, the two relationships, collaboration and antagonism, coexist among agents in natural or engineering scenarios.[47] For example, in the multirobot systems, the relationship between a robot and its teammates is collaborative, but between it and its antagonistic alliance's robots are antagonistic. In biological systems, a pair of genes are viewed as activators when they are in cooperative interaction and inhibitors when in competitive interactions.[48–50] Hence, only discussing one of the interactions of MASs is incomplete. Altafini[51] investigated both cooperative and competitive relationships of MASs and proposed a bipartite consensus (BC) control protocol to govern two opposite alliances to achieve the opposite states, where the agents of an alliance have the same state. Inspired by this result, the BC issues have attracted numerous researchers, and many effective methods[52–55] have been developed for MASs. Wu et al.[52] proposed a distributed consensus control method for MASs to perform the quantized adaptive finite-time BC tracking tasks. The parametric uncertainties, input disturbances, and quantized data were discussed for networked robotic systems to realize BC in the work of Ding et al.[53] Moreover, the designed BC control schemes for unknown dynamics MASs by employing the MFAC and the RL were studied in works of Liang et al.[54] and Peng et al.,[55] respectively. Obviously, the BC problem for MASs forms the second motivation of this paper.

From the above discussions, this paper employs the dynamic linearization method to establish a series of equivalent linear data models for MASs, where only the measurement I/O data of the controlled plant and its neighborhood are necessary. Then, a quantized data-driven distributed bipartite formation control (QDBFC) protocol is proposed for unknown dynamics detected-time nonlinear MASs with fixed and switching topologies to implement bipartite formation tracking tasks under data saturation and quantization. Here, all agents can track the predicted trajectory and achieve the expected formation, even if only a few agents can directly receive the information from the leader. The main contributions and challenges of this paper are listed as follows:

1. Propose a QDBFC approach for unknown dynamics discrete-time nonlinear MASs with antagonistic interactions to implement bipartite formation tracking tasks by only employing measurable I/O data without requiring any prior information. Although several effective algorithms[8–13] have been developed for the formation tracking problem, these methods depend on accurate dynamics, which is not essay to be established.
2. Compared with the existing DDC approaches,[38,39] the designed controller can use fewer data to guarantee the convergence of MASs because its feedback information is incomplete caused by data quantization and saturation. Hence, the proposed scheme requires less consumption of communication and computing resources.
3. The designed protocol has a strong adaptive ability to regulate the MASs to implement bipartite formation tasks under a fixed topology and switching topologies.

The rest work of this paper is structured as follows. Several necessary preliminaries are presented in Section "Preliminary and system description". Section "Controller development and analysis" introduces the proposed QDBFC algorithm for MASs with fixed and switching topologies and offers rigorous proof. The simulation experiments are shown in Section "Simulation studies". The hardware testing is presented in Section "Hardware experiments". Finally, conclusions are given in Section "Conclusions".

Notations:R, Z^+, $R^{N\times N}$, I stand for the set of real numbers, positive integers, $N\times N$ matrices, and identify matrices with arbitrary dimension, respectively. $diag(\bullet)$ denotes the diagonal matrix, and $\|\Theta\|$ denotes the Euclidean norm for a vector Θ. Moreover, S_N denotes the set of agents.

Preliminary and system description

Signed graph theory

Let $F=(V_F, \varepsilon_F, A_F)$ stand for a weighted directed graph. $V_F=V_{F1}\cup V_{F2}=\{1, \ldots, N\}$ denotes the vertex set of F, where all of the vertexs are divided into two subsets V_{F1} and V_{F2}. $S=diag(s_1, \ldots, s_N)$ denotes the grouping matrix. If agent $i\in V_{F1}$, $s_i=1$; Otherwise, $s_i=-1$. $\varepsilon_F=V_F\times V_F$ is the edges set, where $(j, i)\in\varepsilon_F$ denotes an edge between agents i and j, that is, agent j is a neighbor of agent i. All neighbors of agent i is represented by $N_i=\{j\in V_F|(j, i)\in\varepsilon_F\}$. Moreover, $A_F=[a_{ij}]\in R^{N\times N}$ expresses the weighted adjacency matrix of F, where a_{ij} with elements -1, 0, 1 denotes the weighted of edge (j, i). Let $D_F=diag(d_1, \ldots, d_N)$ denote the in-degree of agent i, where $d_i=\sum_{j\in N_i}|a_{ij}|$. Then, the Laplacian matrix of F can be calculated as $L=D_F-A_F$. Considering the virtual leader 0, the graph F becomes $\bar{F}=(\bar{V}_F, \bar{\varepsilon}_F, A_F)$, where $\bar{V}_F=V_F\cup\{0\}$ and $\bar{\varepsilon}_F=\bar{V}_F\times\bar{V}_F$. All of edges between the virtual leader and agents are represented by $B = diag(b_1, \ldots, b_N)$. If the edge between the virtual leader and agent i is existing, $b_i = 1$; otherwise $b_i = 0$. Furthermore, to consider the switching topologies of the MASs, the graph $\bar{F}$ becomes $\bar{F}(k) = (\bar{V}_F(k), \bar{\varepsilon}_F(k), A_F(k))$. In this case, $A_F(k) = [a_{ij}^l(k)] \in R^{N \times N}$, $D_F(k) = diag(d_1^l(k), \ldots, d_N^l(k))$, $S(k) = diag(s_1^l(k), \ldots, s_N^l(k))$, $B^l(k) = diag(b_1^l, \ldots, b_N^l)$, and $l \in \{1, 2, \ldots, \kappa\}$ with $\kappa \in Z^+$. In addition, all possible topologies of the MASs are represented by $\bar{F}^l \in \{\bar{F}^1, \ldots, \bar{F}^\kappa\}$. In this paper, the communication topologies of the MASs are shown in Figure 1. Besides, a piecewise function of topologies of the MASs is defined as

$$\begin{cases} \bar{F}^1, & 0 \leq k \leq 450 \\ \bar{F}^2, & 450 < k \leq 900 \\ \bar{F}^3, & 900 < k \leq 1600 \end{cases} \tag{1}$$

System description

A class of unknown single-input-single-output SISO) nonlinear discrete-time MASs with N agents is investigated, and the nonlinear dynamics of the *ith* agent is considered as

$$\begin{aligned} y_i(k+1) = & f_i(y_i(k), \ldots, y_i(k-n_y), \\ & u_i(k), \ldots, u_i(k-n_u)) \end{aligned} \tag{2}$$

where k is the time instant, $i \in S_N$. n_y, n_u are unknown positive integers. $u_i(k) \in R$ and $y_i(k) \in R$ are the control input and output of agent i at time instant k, respectively. $f_i(\bullet)$ denotes an unknown nonlinear function, and the communication topology of the

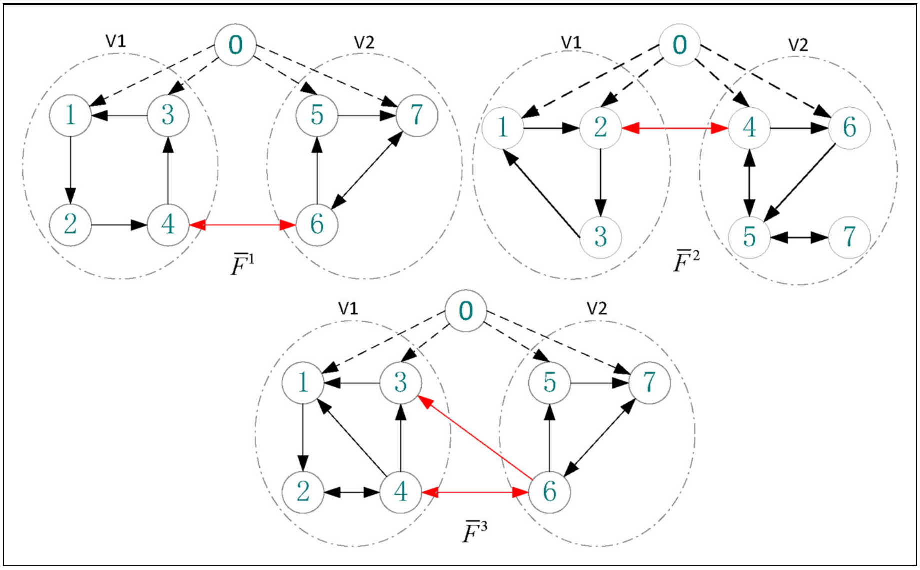

Figure 1. Communication topologies of MASs.

MASs is expressed by $\bar{F} = (\bar{V}_F, \bar{\varepsilon}_F, A_F)$.

The following assumptions with respect to the agent's dynamics are fundamental conditions of the further proposed approach.

Assumption 1. $\partial f_i(\bullet)/\partial u_i(k)$ is continuous.

Assumption 2. equation (2) satisfies the generalized Lipschitz condition that $|\Delta y_i(k+1)| \leq r|\Delta u_i(k)|$ holds for all k, where r is a positive constant, $\Delta y_i(k+1) = y_i(k+1) - y_i(k)$, and $\Delta u_i(k){=}u_i(k) - u_i(k-1) \neq 0$

Remark 1. Assumptions 1 and 2 are basic requirement of the MFAC methods, where the rationalities of them are discussed in published papers.[18,34,38]

Lemma 1(see literature[17,38]). Considering equation (1) satisfies Assumptions 1 and 2, then the following dynamic linear data model can be obtained.

$$\Delta y_i(k+1) = \Gamma_i(k)\Delta u_i(k) \tag{3}$$

where $\Gamma_i(k)$ is called as time-varying pseudo partial derivative parameter with $|\Gamma_i(k)| \leq r$ that r is a small positive constant.

Remark 2. From equation (3), it is noted that $\Gamma_i(k)$ is only dependent on the I/O gain of the controlled plant. Therefore, according to the values of $\Gamma_i(k)$, we can obtain a series of equivalent linear model for the controlled system.

Then, the two important assumptions of the controller are given below.

Assumption 3. For all k and $i \in S_N$, $\Gamma_i(k) > \bar{\sigma} > 0$ $(\Gamma_i(k) < -\bar{\sigma} < 0)$ holds, where $\bar{\sigma}$ is an arbitrarily small positive constant. According to the analysis in existing results,[17,38] we assume $\Gamma_i(k) > \bar{\sigma} > 0$.

Assumption 4. $\bar{F}$ and $\bar{F}^l$ are strongly connected, that is, there is at least one path between the leader and each follower, and the $L+B$ of $\bar{F}$ and $L(k){+}B(k)$ of $\bar{F}^l$ are irreducible matrices.[56]

The objective of the proposed QDBFC approach is to develop an appropriate control protocol $u_i(k)$ to track the desired trajectory with a predicted pattern, where $u_i(k)$ is only dependent on the I/O data of agent i and its neighbors.

Definition 1. For each agent i, if

$$\lim_{k\to\infty}\big(y_i(k) - s_i y_0(k)\big){=}V_i(k) \tag{4}$$

where $y_0(k)$ is the position of the virtual leader 0, and $V_i(k)$ is the desired deviation from agent i to the virtual leader, the bipartite formation tracking task is realized. For the convergence of analysis, For the convergence of analysis, let $e_i(k) = s_i y_0(k) - \tilde{y}_i(k)$ denotes the bipartite formation tracking error of agent i, where $\tilde{y}_i(k) = y_i(k) - V_i(k)$.

Sensor saturation. In practice, the output $y_i(k)$ of MASs is measured by sensors. It is noted that the sensors are unlikely to measure unlimited signals, and the saturation nonlinear phenomenon is inevitable because of the hardware constraints such that the actual output of agents are not available for the controller, that is, to update the state of $u_i(k)$ is dependent on the saturated data.

In this paper, the sensor saturation is modeled as

$$y_{zi}(k) = saty_z(y_i(k)) = \begin{cases} -y_z, & y_i(k) \leq -y_z \\ y_i(k), & -y_z < y_i(k) < y_z \\ y_z, & y_i(k) \geq y_z \end{cases} \tag{5}$$

where $y_{zi}(k)$ is the measured output of agent i, $[-y_z, y_z]$ is the maximum measurement range of the sensor i, and y_z is an unknown positive constant.

Assumption 5. The desired trajectory locate within the measurable range of sensors. i.e., the condition $|y_0(k)| < y_z$ satisfies for all k .

Remark 3. From equation (5), it is noted that the measured input $y_i(k)$ cannot exceed the range of $[-y_z, y_z]$, that is, the measurable range of the sensor is limitation. In the practical industrial process, this saturation nonlinearity feature widely exists in equipment and devices. Hence, it is a meaningful investigation.

Information quantization. Roughly speaking, the agents transmit or receive information from each other dependent on cable or wireless networks. Since the restrictions on the bandwidth of the communication channel, the measured output $y_{zi}(k)$ needs to be quantized before it is transmitted to the controller through the communication channel. Generally, the type of quantizer is selected as the logarithmic type, which is described as

$$U = \left\{\pm h_p : h_p = \theta^p h_0, p = 0, \pm 1, \pm 2, \ldots\right\} \cup \{0\}, \tag{6}$$

where $h_0 > 0$, and θ with $0 < \theta < 1$ is quantization density parameter.

In this paper, the quantizer is described as

$$q(x) = \begin{cases} h_p, & \frac{1}{1+\alpha} h_p < x \leq \frac{1}{1-\alpha} h_p \\ 0, & x = 0 \\ -q(-x), & x < 0 \end{cases} \tag{7}$$

where $\alpha = (1-\theta)/(1+\theta)$. It is noted that the quantizer (7) is time-invariant, $q(-x) = -q(x)$ and $0 < \alpha < 1$.

To this end, this paper aims to design a robust control protocol such that MASs can perform bipartite formation tracking tasks, and the tracking errors of each agent can converge to the origin when k tends to infinity.

Controller development and analysis

Figure 2 shows a diagram of the unknown dynamics MASs controlled by the proposed QDBFC method, where we can see that the saturation phenomenon happens in sensor

i. Besides, the measured output gain $\Delta y_{zi}(k){=}y_{zi}(k) - y_{zi}(k-1)$ and measured output error $\varepsilon_i(k)$ are quantized before they are transmitted to the controller, respectively. Obviously, the stability of the MASs is affected by sensor saturation and information quantization.

Data-driven distributed controller design

Let $\xi_i(k)$ denote the measured or received information at the kth time instant of the ith agent. It is defined as

$$\begin{aligned}\xi_i(k) = \sum_{j\in N_i} |a_{ij}|\left(sign\left(a_{ij}\right)\tilde{y}_j(k) - \tilde{y}_i(k)\right) \\ + b_i(s_i y_0(k) - \tilde{y}_i(k))\end{aligned} \tag{8}$$

where $b_i{=}1$ if agent i can access the desired trajectory, i.e., $\{0, j\} \in \tilde{\varepsilon}$, that is, there is an edge from the virtual leader to agent i; otherwise $b_i{=}0$. Then, the QDBFC algorithm is designed as

$$\begin{aligned}\hat{\Gamma}_i(k) =&\hat{\Gamma}_i(k-1) + \frac{\eta\Delta u_i(k-1)}{\mu + |\Delta u_i(k-1)|^2} \\ &(q_{\Delta i}(\Delta y_{zi}(k)) - \hat{\Gamma}_i(k-1)\Delta u_i(k-1))\end{aligned} \tag{9}$$

$$\begin{aligned}\hat{\Gamma}_i(k) = \hat{\Gamma}_i(1), \;\; if \;\; |\hat{\Gamma}_i(k)| \le c \;\; or \;\; |\Delta u_i(k-1)| \le c \\ or \;\; sign(\hat{\Gamma}_i(k)) \ne sign(\hat{\Gamma}_i(1))\end{aligned} \tag{10}$$

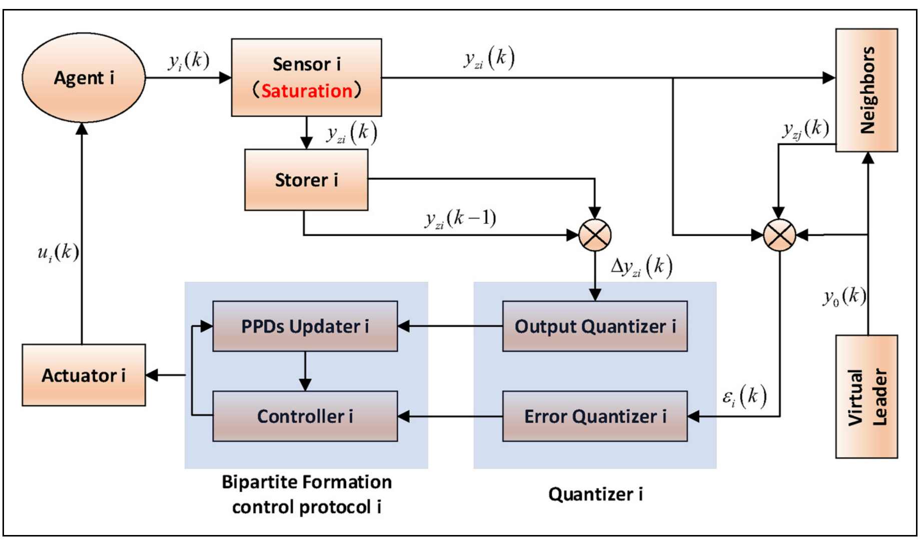

Figure 2. Diagram of agent *i* with the QDBFC scheme.

$$u_i(k) = u_i(k-1) + \frac{\rho \hat{\Gamma}_i(k)}{\lambda + |\hat{\Gamma}_i(k)|^2} \xi_{qzi}(k) \tag{11}$$

where $\Delta y_{zi}(k) = y_{zi}(k) - y_{zi}(k-1)$, $0 < \eta \leq 1$, and $\mu > 0$. ρ and λ are stability parameters, and they will be considered later on. $\hat{\Gamma}_i(k)$ is the estimated value of $\Gamma_i(k)$, and $\hat{\Gamma}_i(1)$ is the initial state. c is a threshold and is often selected as 10^{-3} or 10^{-4}. $\xi_{qzi}(k)$ is the quantized $\xi_i(k)$, presented later on.

Remark 4. It is noted that equation (8) only employs the measured output of agent i and agent i's neighbors, $i \in S_N$. Moreover, some agents even cannot be controlled by the virtual leader directly when b_i=0. Therefore, the proposed QDBFC doesn't need full information from the entire network, which is a distributed algorithm and can reduce the information transmission costs.

Remark 5. It is noted that $\hat{\Gamma}_i(k)$ is updated by employing $\Delta u_i(k-1)$ and quantized $\Delta y_{zi}(k)$. The control law (11) is updated by using the quantized distributed combined measurement error $\xi_{qzi}(k)$. Furthermore, the proposed algorithm doesn't apply any dynamics information of MASs. Hence, the proposed algorithm is a data-driven distributed approach. Comparing with the related DDC methods,[38,40] it is more complicated and robust.

Saturation issues analysis

To analysis sensor saturation issues, we define that the measured output error $\varepsilon_i(k) = y_{si}(k) - y_{zi}(k)$, where $y_{si}(k)$=$s_i y_0(k)$+$V_i(k)$. Then, we have

$$\varepsilon_i(k) = e_i(k)\, p_i(k) \tag{12}$$

where

$$p_i(k) = \begin{cases} c\frac{y_{si}-y_z}{e_i(k)}, & e_i(k) < y_{si} - y_z \\ 1, & y_{si} - y_z \leq e_i(k) \leq y_{si} + y_z \\ \frac{y_{si}+y_z}{e_i(k)}, & e_i(k) > y_{si} + y_z \end{cases} \tag{13}$$

and it is obvious that $0 < p_i(k) \leq 1$. Then, the following lemma is obtained.

Lemma 2(see the work of Bu et al.[40]). Suppose that MASs are affected by the sensor saturation presented in equation (5). The relationship between the accurate and measured output gain of sensor i can be described as $\Delta y_{zi}(k) = g_i(k)\Delta y_i(k)$, where $0 \leq g_i(k) \leq 1$.

Quantization issues analysis

From the work of Fu et al.[57], it is obtained that the quantization problem can be seen as a sector-bound uncertain problem, that is, the given signal x and the quantizer $q(x)$ can be described as $q(x)$=$(1+\Delta(x))x$ with $|\Delta(x)| < \alpha$. Hence, the following Lemma is obtained.

Lemma 3(see the work of Fu et al.[57]). Utilize θ_{zi}, $\theta_{\Delta i}$, and $\theta_{\varepsilon i}$ to denote the quantization density parameters of $q_{zi}(\cdot)$, $q_{\Delta i}(\cdot)$, and $q_{\varepsilon i}(\cdot)$, respectively. Applying the sector bound approach, we have

$$q_{z_i}(y_{zi}(k)) - y_{zi}(k) = \sum\nolimits_{z_i} y_{zi}(k) \tag{14}$$

$$q_{\Delta i}(\Delta y_{zi}(k)) - \Delta y_{zi}(k) = \sum\nolimits_{\Delta i} \Delta y_{zi}(k) \tag{15}$$

$$q_{\varepsilon_i}(\varepsilon_i(k)) - \varepsilon_i(k) = \sum\nolimits_{\varepsilon_i} \varepsilon_i(k) \tag{16}$$

where $|\Sigma_{zi}| \leq \alpha_{zi}$, $|\Sigma_{\Delta i}| \leq \alpha_{\Delta i}$, $|\Sigma_{\varepsilon i}| \leq \alpha_{\varepsilon i}$, $\alpha_{zi} = \frac{1-\theta_{z_i}}{1+\theta_{z_i}}$, $\alpha_{\Delta i} = \frac{1-\theta_{\Delta i}}{1+\theta_{\Delta i}}$, and $\alpha_{\varepsilon i} = \frac{1-\theta_{\varepsilon i}}{1+\theta_{\varepsilon i}}$.

Convergence analysis

In this part, the convergence analysis of the proposed QDBFC approach is presented as below.

Lemma 4(see the work of Yang et al.[56]). For $k = 1, 2, \ldots, Q$, $T(k)$ is a time-varying irreducible substochastic matrix with positive diagonal entries. Then, we can obtain

$$\|T(Q)T(Q-1)\cdots T(1)\| \leq \beta \tag{17}$$

where $0 < \beta < 1$.

Theorem 1. Under the circumstances that equation (2) satisfies Assumptions 1, 2, and 3, its communication topology satisfies Assumption 4, and the measurable range of each sensor satisfies Assumption 5, apply the proposed QDBFC algorithm equation (9)-(11) for MASs to track the desired reference trajectory $y_0(k) = constant$. If ρ satisfies the following condition

$$\rho < \frac{1}{\max_{i \in S_N} \left(\sum_{j=1}^{N} |a_{ij}| + b_i \right)}$$

and $\lambda > r^2/4$, the tracking error satisfies that $\lim_{k \to \infty} \|e(k+1)\| = 0$.

Proof.. The proof comprises the following two steps.

Step 1 (The boundedness of $\hat{\Gamma}_i(k)$): Let $\tilde{\Gamma}_i(k) = \hat{\Gamma}_i(k) - \Gamma_i(k)$ and $\Delta\Gamma_i(k) = \Gamma_i(k) - \Gamma_i(k-1)$. From Lemmas 2 and 3, Eqs. (9) and (15), we have

$$\begin{aligned}\tilde{\Gamma}_i(k) &= \tilde{\Gamma}_i(k-1) - \Delta\Gamma_i(k) + \frac{\eta\Delta u_i(k-1)}{\mu + |\Delta u_i(k-1)|^2} \\ &\quad \times \left(q_{\Delta i}(\Delta y_{zi}(k)) - \hat{\Gamma}_i(k-1)\Delta u_i(k-1)\right) \\ &= \left(1 - \frac{\eta\Delta u_i(k-1)^2}{\mu + |\Delta u_i(k-1)|^2}\right)\tilde{\Gamma}_i(k-1) - \Delta\Gamma_i(k) \\ &\quad + \frac{\eta\Gamma_i(k-1)\Delta u_i(k-1)^2}{\mu + |\Delta u_i(k-1)|^2} g_i(k)\left(\sum\nolimits_{\Delta i} - 1\right)\end{aligned} \tag{18}$$

Then, we can obtain

$$\begin{aligned}\left|\tilde{\Gamma}_i(k)\right| &\le \left|1 - \frac{\eta\Delta u_i(k-1)^2}{\mu + |\Delta u_i(k-1)|^2}\right|\left|\tilde{\Gamma}_i(k-1)\right| + |\Delta\Gamma_i(k)| \\ &\quad + \left|\frac{\eta\Delta u_i(k-1)^2}{\mu + |\Delta u_i(k-1)|^2}\right||\Gamma_i(k-1)|\left|g_i(k) - 1\right| \\ &\quad + \left|\frac{\eta\Delta u_i(k-1)^2}{\mu + |\Delta u_i(k-1)|^2}\right||\Gamma_i(k-1)|\left|\sum\nolimits_{\Delta i}\right|\left|g_i(k)\right|\end{aligned} \tag{19}$$

Since $0 < \eta \le 1$ and $\mu > 0$, we can obtain that

$$0 < \frac{\eta\Delta u_i(k-1)^2}{\mu + |\Delta u_i(k-1)|^2} < 1 \tag{20}$$

Then, we can select a constant $\wp$ properly to fit that

$$0 < \left|1 - \frac{\eta\Delta u_i(k-1)^2}{\mu + |\Delta u_i(k-1)|^2}\right| \le \wp < 1 \tag{21}$$

According to $|\Gamma_i(k)| \le r$, $0 \le g_i(k) \le 1$, Lemma 4, and Eqs. (19)-(21), we have

$$\begin{aligned}\left|\tilde{\Gamma}_i(k)\right| &\le \wp\left|\tilde{\Gamma}_i(k-1)\right| + 2r + r + r \\ &\le \wp\left(\wp\left|\tilde{\Gamma}_i(k-2)\right| + 4r\right) + 4r \\ &\quad \cdots \\ &\le \wp^{k-1}\left|\tilde{\Gamma}_i(1)\right| + \frac{\left(1 - \wp^{k-1}\right)}{\left(1 - \wp\right)} 4r\end{aligned} \tag{22}$$

Hence, we can obtain that $\lim_{k\to\infty} |\tilde{\Gamma}_i(k)| = 4r/(1 - \wp)$, that is, $\tilde{\Gamma}_i(k)$ is bounded. Meanwhile, according to that $\Gamma_i(k)$ is bounded, we have that $\hat{\Gamma}_i(k)$ is bounded.

Step 2 (The convergence of $e(k)$): Since MASs suffer the sensor saturation and data quantization, according to Eqs. (8) and (12), we obtain that

$$\begin{aligned}\xi_{qzi}(k) = &\sum_{j\in N_i}\left(\left|a_{ij}\right|q_{\varepsilon i}(\varepsilon_i(k)) - a_{ij}q_{\varepsilon j}\left(\varepsilon_j(k)\right)\right)\\ &+ b_i q_{\varepsilon i}(\varepsilon_i(k))\end{aligned} \tag{23}$$

Define the following collective stack vectors:

$$\begin{aligned}
u(k) &= [u_1(k), u_2(k), \ldots, u_N(k)]^T\\
\xi_{qz}(k) &= \left[\xi_{qz_1}(k), \xi_{qz_2}(k), \ldots, \xi_{qz_N}(k)\right]^T\\
e(k) &= [e_1(k), e_2(k), \ldots, e_N(k)]^T\\
p(k) &= \left[p_1(k),\ p_2(k),\ \ldots,\ p_N(k)\right]^T\\
q_\varepsilon(k) &= \left[q_{\varepsilon 1}(k), q_{\varepsilon 2}(k), \ldots, q_{\varepsilon N}(k)\right]^T\\
\varepsilon(k) &= [\varepsilon_1(k), \varepsilon_2(k), \ldots, \varepsilon_N(k)]^T
\end{aligned}$$

equation (23) can be written in a compact form

$$\xi_{qz} = (L+B)q_\varepsilon(\varepsilon(k)) = (L+B)\left(\varphi(k)+I\right)\varepsilon(k) \tag{24}$$

where $\varphi(k)=diag(\Sigma_{\varepsilon 1}, \ldots, \Sigma_{\varepsilon N})$. Then, from equation (24), the compact form of the control law (11) can be written as

$$u(k) = u(k-1) + \rho\Omega(k)(L+B)\left(\varphi(k)+I\right)\varepsilon(k) \tag{25}$$

where

$$\Omega(k) = diag\left(\frac{\hat{\Gamma}_1(k)}{\lambda + |\hat{\Gamma}_1(k)|^2}, \ldots, \frac{\hat{\Gamma}_N(k)}{\lambda + |\hat{\Gamma}_N(k)|^2}\right)$$

According to equation (3), equation (12), $e_i(k) = s_i y_0(k) - \tilde{y}_i(k)$, $\tilde{y}_i(k)=y_i(k) - V_i(k)$, and $y_0(k) = constant$, we can obtain

$$\begin{aligned}e(k+1) &= e(k) - \rho\Psi(k)(L+B)e(k)\,p(k)\left(\varphi(k)+I\right)\\ &= \left(I - \rho\Xi(k)\right)e(k)\end{aligned} \tag{26}$$

where $\Psi(k)=diag(\vartheta_1(k), \ldots, \vartheta_N(k))$, $\vartheta_i(k) = \frac{\Gamma_i(k)\hat{\Gamma}_i(k)}{\lambda+|\hat{\Gamma}_i(k)|^2}$, and $\Xi(k) = \Psi(k)(L+B)p(k)(\varphi(k)$ $+I)$. According to Assumption 3, Lemma 1, and $\lambda > r^2/4$, we have

$$0 < \vartheta_i(k) = \frac{\Gamma_i(k)\hat{\Gamma}_i(k)}{\lambda + |\hat{\Gamma}_i(k)|^2} \le \frac{r\hat{\Gamma}_i(k)}{2\sqrt{\lambda}|\hat{\Gamma}_i(k)|} < \frac{r}{2\sqrt{r^2/4}} = 1$$

Then, according to Lemma 3, $0 < \vartheta_i(k) < 1$, $0 < p_i(k) \leq 1$, ρ satisfying

$$\rho < \frac{1}{\max_{i \in S_N} \sum_{j=1}^{N} |a_{ij}| + b_i}$$

and the analyses,[38,54] we obtain that $\rho\Xi(k) - I$ is an irreducible substochastic matrix with positive diagonal entries. From equation (26), we have

$$\begin{aligned} \|e(k+1)\| &= \left\|\rho\Xi(k) - I\right\| \|e(k)\| \\ &\leq \left\|\rho\Xi(k) - I\right\| \left\|\rho\Xi(k-1) - I\right\| \|e(k-1)\| \\ &\quad \cdots \\ &\leq \left\|\rho\Xi(k) - I\right\| \left\|\rho\Xi(k-1) - I\right\| \cdots \\ &\quad \left\|\rho\Xi(k) - I\right\| \|e(1)\| \end{aligned} \tag{27}$$

Then, employing Lemma 4, we can obtain that

$$\lim_{k \to \infty} \|e(k+1)\| = \lim_{k \to \infty} \left(\beta^{\left\lfloor \frac{k}{Q} \right\rfloor} \|e(1)\|\right)$$

where $\lfloor \bullet \rfloor$ denotes the floor function. Since $0 < \beta < 1$, $\lim_{k \to \infty} \|e(k+1)\| = 0$.

Extension to switching topologies

In this part, time-varying switching topologies are discussed. The convergence of MASs to perform formation tracking tasks is investigated.

According to the signed graph theory of Section 2, Eq (23) becomes

$$\begin{aligned} \xi_{qzi}(k) = &\sum_{j \in N_i} \left(\left|a_{ij}^l(k)\right| q_{\varepsilon i}(\varepsilon_i(k)) - a_{ij}^l(k) q_{\varepsilon j}\left(\varepsilon_j(k)\right)\right) \\ &+ b_i^l(k) q_{\varepsilon i}(\varepsilon_i(k)) \end{aligned} \tag{28}$$

Theorem 2. For the MASs satisfying Assumptions 1-5, the value of ρ satisfies

$$\rho < \frac{1}{\max_{i \in S_N, l=1,2,\ldots,\kappa} \sum_{j=1}^{N} |a_{ij}^l(k)| + b_i^l(k)}$$

and $\lambda > r^2/4$, applying laws Eqs. (8)-(10) of the QDBFC method can achieve the bipartite formation objective equation (4) as $k \to \infty$.

Proof.. According to equation (28), equation (26) becomes

$$\begin{aligned} e(k+1) = &\left(I - \rho\Psi(k)(L(k) + B(k))\right. \\ &\left. p(k)\left(\varphi(k) + I\right)\right) e(k) \end{aligned} \tag{29}$$

where all reciprocals of the diagonal entries in $L(k) + B(k)$, $l = 1, 2, \ldots, \kappa$, are larger than ρ. Hence, using the similar analysis methods in Theorem 1, we can obtain that $\rho\Psi(k)(L(k)+B(k))\,p(k)(\varphi(k){+}I)-I$ is an irreducible substochastic matrix, and their diagonal entries are positive. Meanwhile, we also can prove that $\lim_{k\to\infty}\|e(k+1)\|{=}0$.

Remark 6. Most of the existing consensus algorithms or formation algorithms for MASs depend on the assumption that the accurate mathematical models of the MASs are available. However, it is noted that the mathematical models are not a requirement in the proposed QDBFC algorithm. Moreover, the existing data-driven approaches[38–40] for MASs don't consider the data quantization, sensor saturation, and switching topologies problems together. Hence, compared with existing works, the design, convergence proof, and simulations of the proposed controller become more challenging.

Simulation studies

To illustrate the correctness and practicality of the proposed QDBFC approach, two examples are presented for seven agents to implement bipartite formation tracking tasks. It is noted that consensus control is a special format of formation control, when $V_i(k)=0$ with $i=1, 2, 3, 4, 5, 6, 7$. In addition, all of the possible communication topologies of MASs are presented in Figure 1, and all of the formation parameters are presented in Table 1.

Fixed topology of MASs

In this simulation, we select $\bar{F}^1$ as the communication topology of MASs shown in Figure 1, where the virtual leader is expressed by vertex 0, and only agents 1, 3, 5, and 7 can directly receive the information from the virtual leader. Moreover, the information among agents only transmits along with the arrows, that is, the direction of transmitting information is fixed. Although some agents cannot directly receive the virtual leader's information, the proposed QDBFC is a distributed approach, and the communication graph is strongly connected such that the virtual leader can effectively govern each agent.

According to the communication topology $\bar{F}^1$, we can obtain that the reciprocal of the greatest diagonal entry of $L+B$ is 0.5. To satisfy the convergence condition for all $i=$

Table 1. The formation parameters of multi-agent systems (MASs)

Processes	$0<k<450$		$450\leq k<900$		$900\leq k<1600$	
Examples	1	2	1	2	1	2
$y_0(k)$	5	5	10	10	15	15
$V_1(k)$	0	0	2	−2	2	0
$V_2(k)$	0	0	4	2	4	2
$V_3(k)$	0	0	6	4	6	−2
$V_4(k)$	0	0	0	6	0	4
$V_5(k)$	0	0	−2	−2	−2	6
$V_6(k)$	0	0	−4	−4	−4	−4
$V_7(k)$	0	0	−6	−6	−6	−6

1, 2, 3, 4, 5, 6, 7 in Theorem 1, the controller parameters are selected as $\rho = 0.3$, $\mu = 0.5$, $\eta = 1$, $\lambda = 1$, and $c = 10^{-4}$. Meanwhile, the initial conditions are chosen as $u_i(0) = 0$, $\Gamma_i(1) = 2$, and $y_i(0)= rand(-0.005, 0.005)$ for all agents in this simulation. Moreover, the formation parameters of this example shown in Table 1, and agents are governed by

$$\begin{aligned}
Agent1 : y_1(k+1) &= y_1(k)/(1 + y_1^2(k)) + 0.5u_1^2(k),\\
Agent2 : y_2(k+1) &= 1.63y_2(k) - 0.64y_2(k-1)\\
&\quad - 0.92u_2(k-1) + 1.22u_2(k),\\
Agent3 : y_3(k+1) &= 1.61y_3(k) - 0.62y_3(k-1)\\
&\quad - 0.88u_3(k-1) + 1.19u_3(k),\\
Agent4 : y_4(k+1) &= 1.59y_4(k) - 0.60y_4(k-1)\\
&\quad - 0.95u_4^2(k-1) + 1.23u_4(k),\\
Agent5 : y_5(k+1) &= \frac{y_5(k)u_5(k)}{(1 + y_5(k-1))} + 0.8u_5^4(k),\\
Agent6 : y_6(k+1) &= 1.58y_6(k) - 0.62y_6(k-1)\\
&\quad - 0.90u_6(k-1) + 1.18u_6(k),\\
Agent7 : y_7(k+1) &= \frac{y_7(k)u_7(k)}{(1 + y_7^2(k-1))} + 0.8u_7^3(k).
\end{aligned}$$

To analyze the robustness of the designed QDBFC method for MASs with fixed topology, we consider three different operating environments for MASs to perform bipartite formation tracking tasks shown in Figures 3 and 4. Firstly, we set MASs without the sensor saturation and set the quantizer's parameters as $\theta = \theta_{zi}=\theta_{\Delta i}=\theta_{\varepsilon i}=0.9$, and then, we set $\theta = \theta_{zi}=\theta_{\Delta i}=\theta_{\varepsilon i}=0.2$ to test the effect of data quantization in Figure 3(a) and (b), respectively. From Figure 4(a) and (b), we find that the valve of θ (θ_{zi}, $\theta_{\Delta i}$, and $\theta_{\varepsilon i}$) affects the convergence rate of the MASs, but it doesn't destroy the stability of the controlled systems. A bigger value of the quantizer's parameters has a faster convergence speed. In Figure 3(c), agents 1-3 suffer to sensor saturation, where $y_z{=}ysi(k){=}\tilde{y}_i(k) + 0.5$ with $i = 1, 2, 3$, and $\theta_{zi} = \theta_{\Delta i} = \theta_{\varepsilon i}=0.2$ with $i = 1, 2, 3, 4, 5, 6, 7$. From Figure 4(c), we notice that the agents suffer to data quantization and sensor saturation. However, the proposed QDBFC still can guarantee that the errors of MASs are cut to the origin.

Moreover, to analyze the characteristics of quantitative communication, a contrast experiment is conducted, where the running environment of the controller consists of "Intel(R) Core(TM) i7-8750H CPU" and "32.0 GB RAM". The corresponding results are shown in Figures 5 and 6, where Figure 5(a) shows the results of the proposed QDBFC method, and Figure 5(b) shows the results of the existing method[38]. Compared with Figure 5(a) and (b), it is found that they have similar performances. However, the total running times of the proposed QDBFC method is about 0.584s, but that of the existing method[38] is about 0.942s. Obviously, compared with the existing method[38], the proposed QDBFC method can save the computation resources.

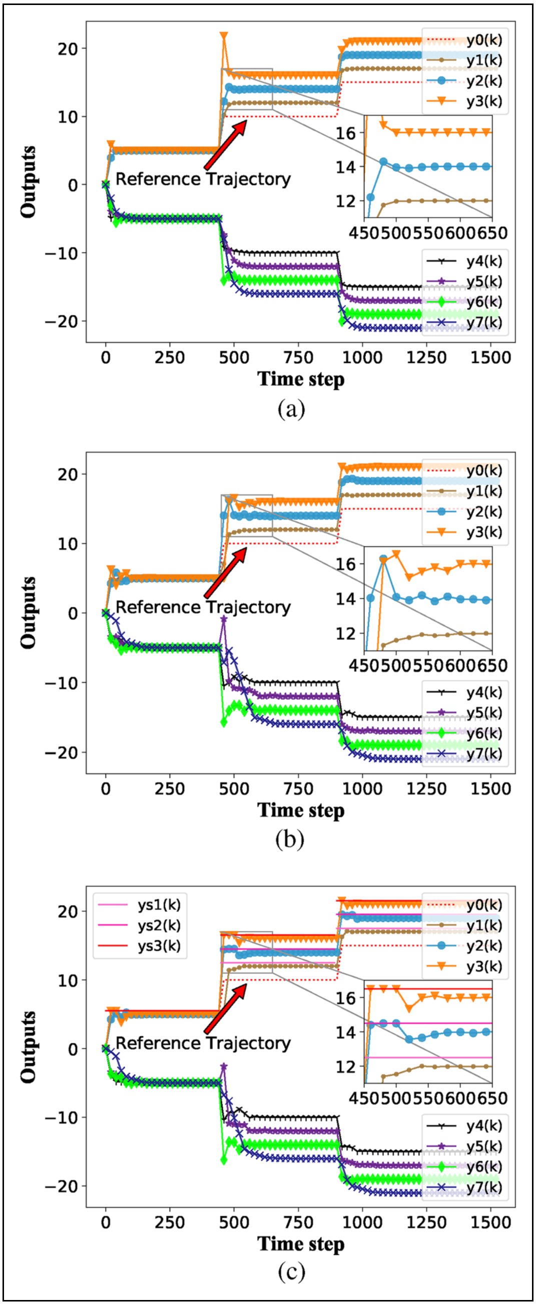

Figure 3. Tracking performances of multi-agent systems (MASs) in Example 1. (a) $\theta = 0.9$; (b) $\theta = 0.2$; (c) $\theta = 0.2$ and suffering saturation.

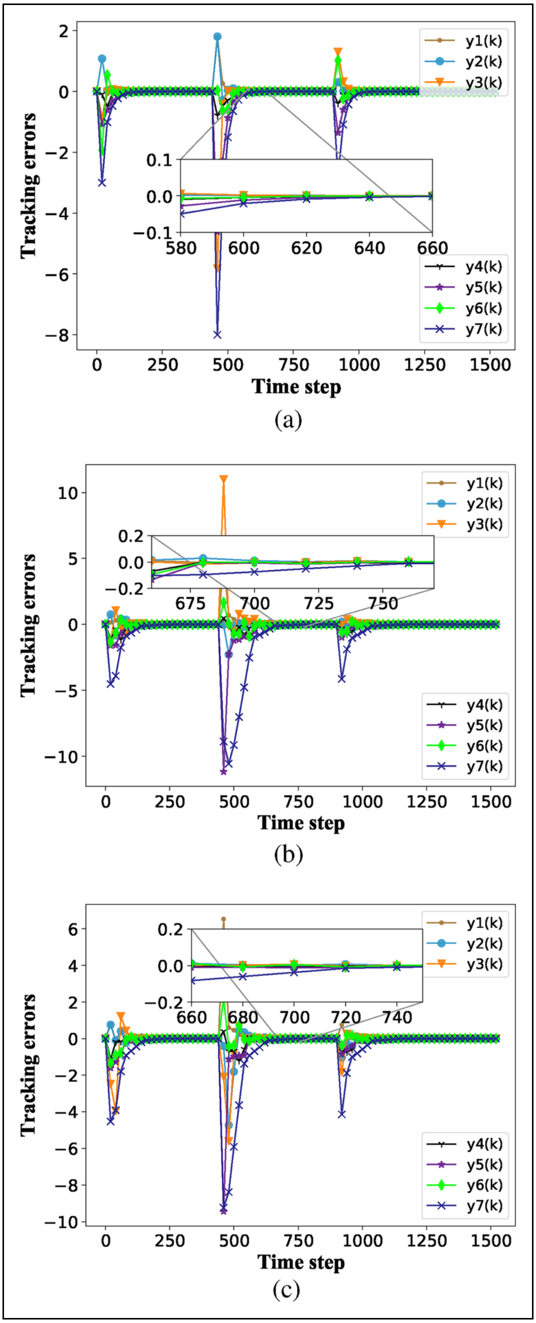

Figure 4. Tracking errors of multi-agent systems (MASs) in Example 1. (a) $\theta = 0.9$; (b) $\theta = 0.2$; (c) $\theta = 0.2$ and suffering saturation.

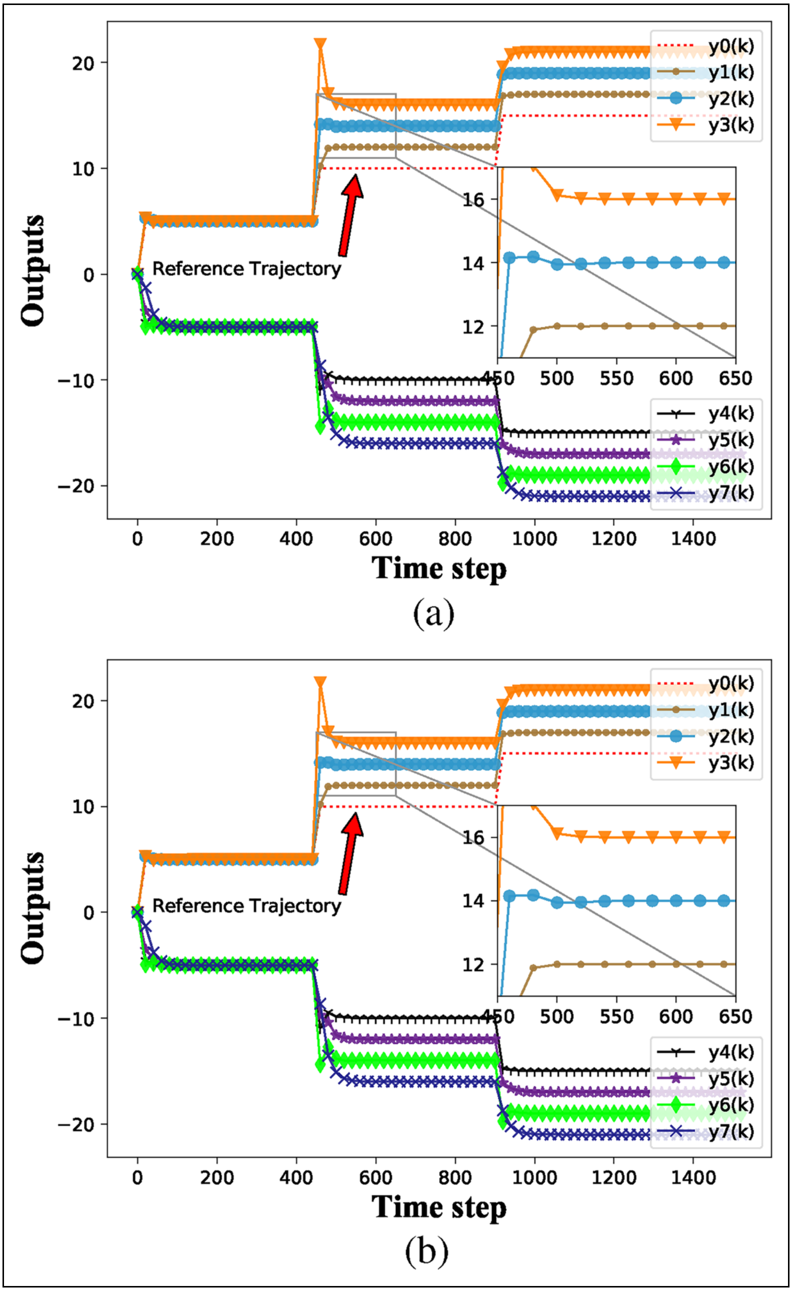

Figure 5. The outputs of the multi-agent systems (MASs) with different methods. (a) The proposed QDBFC method; (b) The existing method[38]

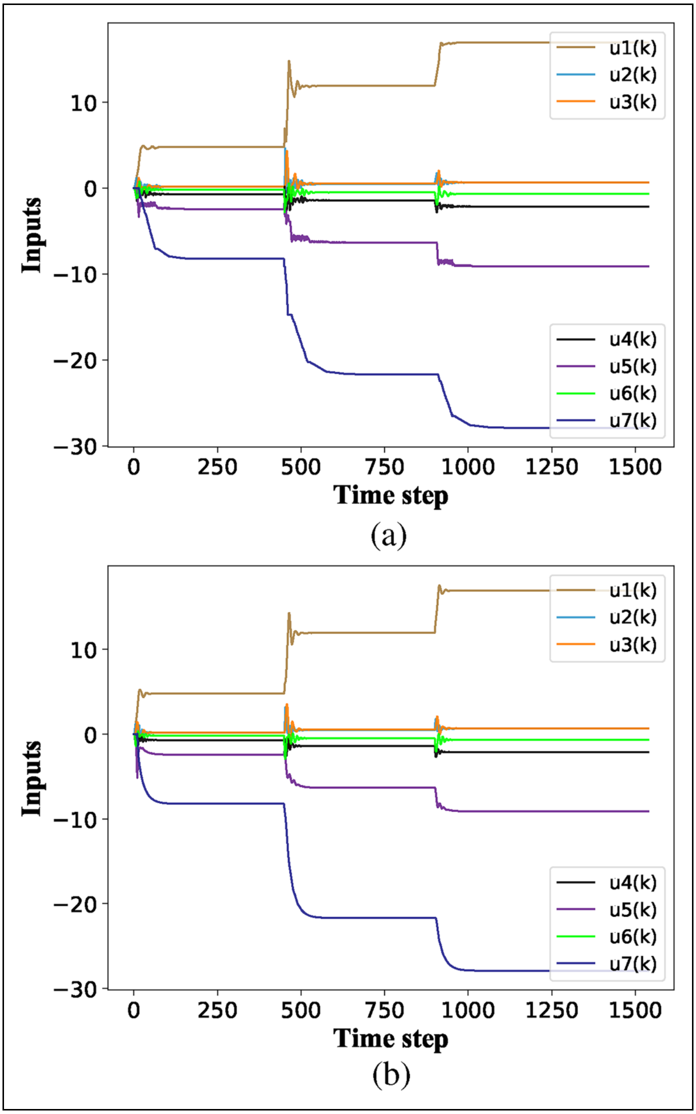

Figure 6. The inputs of the multi-agent systems (MASs) with different methods. (a) The proposed QDBFC method; (b) The existing method[38].

Remark 7. From the dynamics of each agent, it is noted that MASs are heterogeneous, where the dynamics models are only applied to generate the I/O data for the simulation, and in developing QDBFC method, the dynamics models are unknown.

Remark 8. According to Example 1, it is noted that the proposed QDBFC algorithm can address the data quantization and sensor saturation problems for MASs with fixed

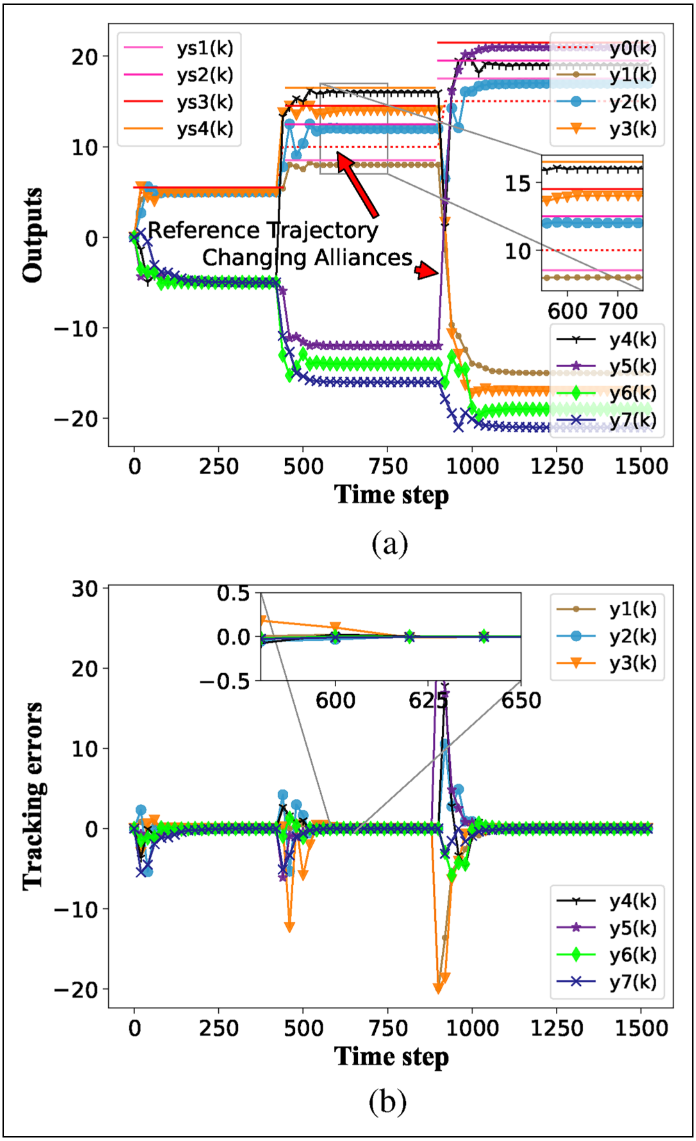

Figure 7. Tracking test of multi-agent systems (MASs) with switching topologies in Example 2. (a) Tracking performance of MASs; (b) Tracking errors of MASs

topology to perform bipartite formation tracking tasks. The proposed method needs lesser computation resources for unknown dynamics heterogeneous discrete-time MASs to perform bipartite formation tracking tasks than that of the existing DDC algorithms.

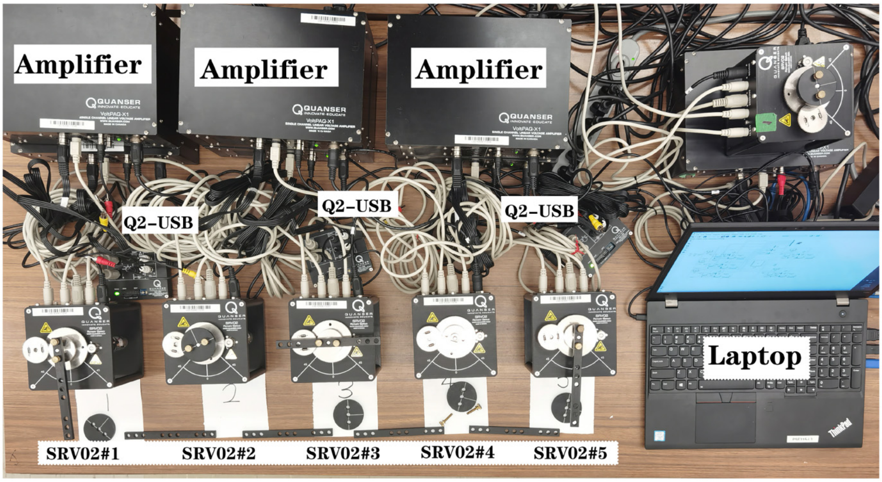

Figure 8. Hardware test platform with five SRVO2.

Time-varying switching topologies of MASs

Here, we consider the switching topologies of MASs shown in Figure 1, changed as equation (1). The dynamics of MASs and related parameters are selected as same as Example 1.

The performance of the proposed QDBFC method to govern the MASs with switching topologies, sensors saturation, and data quantization is presented in Figure 7. From Figure 7(a), we can see that several agents exchange their alliances, but the bipartite formation tracking tasks also can be accomplished. Moreover, from Figure 7(b), we can see that the tracking errors rapidly converge to zero.

This result verifies the effectiveness and correctness of the results in Theorem 2. It also illustrates that the proposed QDBFC approach has good robustness.

Hardware experiments

In this section, a hardware testing system is established, including three Q2-USB data acquisitions, three amplifiers, and five SRV02, shown in Figure 8. The components of the hardware testing system are produced by Quanser. Here, each SRV02 represents a agent. Moreover, from Figure 8, it is found that the construction of each SRV02 is different, so the established MASs is heterogeneous. To verify the effectiveness and practicality of the designed QDBFC method, a contrast experiment is presented in Figure 9, where the topology of MASs is set as Figure 9(a), the sample time is 0.001s, and the total running time is 10s. The initial conditions of each agent is set as $y_1 = 3.0$ rad/s, $y_2 = -2.0$ rad/s, $y_3 = -3.5$ rad/s, $y_4 = 2.0$ rad/s, $y_5 = 2.5$ rad/s. Moreover, $\theta_{zi} = \theta_{\Delta i} = \theta_{\varepsilon i}$=0.5, $ys1(k) = 4.6$ rad/s, $ys2(k) = -4.1$ rad/s, and other parameters are

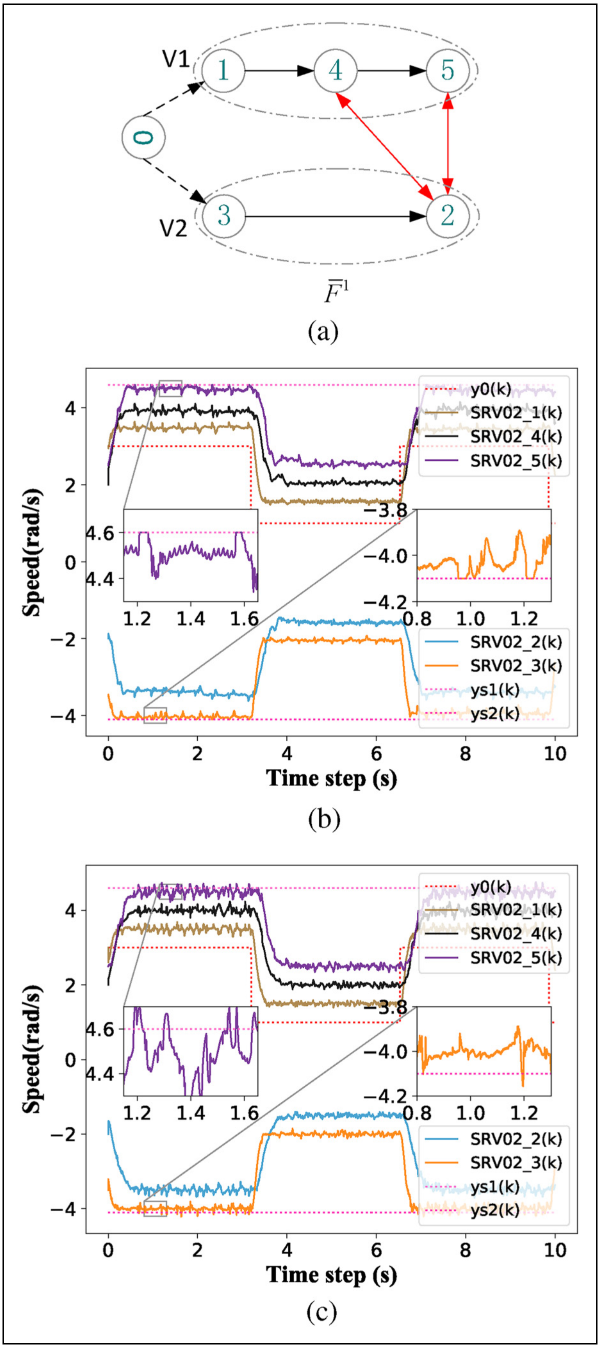

Figure 9. Communication topology and speed of five SRV02. (a) Topology of five SRV02; (b) The proposed scheme; (c) The existing scheme[38]

set as same with Example 1. The desired deviation of each agent is set as $V_1(k) = 0.50$ rad/s, $V_2(k) = -0.50$ rad/s, $V_3(k) = -1.00$ rad/s, $V_4(k) = 1.00$ rad/s, $V_5(k) = 1.50$ rad/s. The reference speed is set as $y_0(k) = 2 - 1*(-1)^{round(3k/10000)}$ rad/s.

Compared with Figure 9(b) and (c), it is found that the proposed method has a similar performance as the existing method.[38] Moreover, it is noteworthy that the output of the designed algorithm is more smooth than the existing algorithm, even if the sensors' measurement range is limited and the data is quantized in the designed algorithm. Hence, the designed approach effectively reduces the computation and communication sources and has good robustness and applicability.

Remark 9. The above simulation and hardware tests show that the proposed approach has good robustness, ensuring the MASs reach and remain a predicted formation when MASs suffer to data quantization, sensor saturation, and switching topologies. Moreover, the dynamics of MASs are unknown, and the collaborative and antagonistic relationships among agents are coexistence, which doesn't affect the convergence property of MASs to perform bipartite formation tracking tasks under governing of the proposed QDBFC scheme.

Conclusions

In this paper, the saturation and quantization issues for nonlinear MASs with antagonistic relationships have been investigated. An equivalent dynamic data model has been established by using the incomplete I/O data caused by limited sensors and communication requirements. A QDBFC scheme has been proposed for the MASs with fixed and switching topologies, which guarantees that the bipartite formation errors of the MASs with incomplete feedback data converge to zero. The efforts of saturation and quantization for the proposed method have been analyzed, showing that the proposed method has good robustness. Compared with existing method, the proposed QDBFC can further reduce communication resources.

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