Prescribed-Time Formation Tracking Control With Collision Avoidance Under Limited Information

Shun Yang, Qiang Xiao, Senior Member, Zhigang Zeng, Fellow, IEEE,

Abstract—In this paper, we address the problem of prescribedtime formation tracking under collision avoidance for a firstorder multi-intelligent system with a directed spanning tree communication topology. By introducing a time-varying function, a new null-space-based of the prescribed-time behavioral control algorithm is proposed for driving all followers to approach the dynamic leader within a prescribed time and guaranteeing no collision among followers. The algorithm can be pre-specified with parameters designed for the user and is independent of the initial conditions or controller parameters. In particular, the velocities of the newly designed behaviors, as an important part of the algorithm, complete the tasks within the prescribed time in a distributed manner respectively. We design a new Lyapunov candidate function and analyze the prescribed-time convergence of the closed-loop system under behavioral conflicts. Finally, the effectiveness of the algorithm is verified by simulation examples with four agents.

Index Terms—Prescribed-time stability, collision avoidance, directed communication, formation tracking control

I. INTRODUCTION

ULTI-AGENT Systems (MAS) have become an integral part of contemporary technological advancements, impacting a myriad of fields such as robotics[1], automated vehicles[2], aerospace[3] and more. MAS consist of multiple interacting agents working collectively to achieve common objectives, thereby demonstrating enhanced efficiency, flexibility, and robustness compared to single-agent systems. The coordinated effort of these agents facilitates complex task execution, surpassing the capabilities of individual agents. Formation control, as an important part of the functionality of MAS, is a pivotal subset that ensures agents maintain a desired formation while navigating dynamic environments[4].

Formation control is paramount in MAS as it enables a group of agents to coordinate their movements, maintaining specific geometric patterns or formations[5]. This coordination is essential for applications like autonomous vehicle platoons, satellite formations, and robotic swarms, where precise alignment and spacing between agents are crucial for achieving overarching goals. However, the practical deployment of MAS in real-environmental scenarios introduces the challenge of

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Q. Xiao, S. Yang, and Z. Zeng are with School of Artificial Intelligence and Automation, the Key Laboratory of Image Processing and Intelligent Control, Huazhong University of Science and Technology, Wuhan 430074, China (email: xq1620128@126.com; shunyang@hust.edu.cn; zgzeng@hust.edu.cn).

collision avoidance. As agents maneuver through environments with varying obstacles and other agents, the risk of collisions becomes a significant concern. Ensuring the safety and efficiency of MAS operations necessitates the integration of robust collision avoidance mechanisms within formation control strategies.

Various methodologies have been developed to address the collision avoidance problem in formation control. Common approaches include the model predictive control (MPC) method[6], artificial potential field (APF) method[7], null-space-based (NSB) behavioral control method[8], and reinforcement learning (RL)[9]. Each of these approaches has its own merits and limitations. The MPC method, for instance, is known for its predictive capabilities and optimal control performance but suffers from high computational demands, making it less practical for real-time applications. The APF method, while simpler and computationally efficient, lacks predictive abilities for collision avoidance and obstacle circumvention. RL, on the other hand, relies heavily on extensive model training and learning, which may not always be feasible or reliable in dynamic environments.

Among these methods, NSB stands out for its predictive capabilities and effective multi-task coordination, leading to its widespread application in robots. This method mitigates the drawbacks of other approaches by projecting low-priority behaviors into the null space of high-priority behaviors that achieve collision avoidance and formation control simultaneously[10].

Research in MAS formation control has evolved to address the stability requirements of these systems. Traditionally, stability in MAS was focused on asymptotic stability[11], where the system's state converges to a desired equilibrium point over time. However, the increasing demand for rapid and reliable convergence has shifted the focus towards prescribed-time stability[12]. Unlike finite-time[13] and fixed-time stability[14], where convergence time is influenced by initial conditions or controller parameters, prescribed-time stability allows for the convergence time to be arbitrarily specified off-line, providing a more predictable and reliable framework for formation tracking.

Despite the advancements in prescribed-time stability, achieving this stability in the presence of collision and obstacle avoidance remains a challenging problem. Current research[15–19] has made significant strides in formation control and collision avoidance, yet there is a notable gap in studies addressing prescribed-time formation control integrated with collision avoidance mechanisms. This gap highlights the

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need for innovative approaches that ensure MAS can achieve prescribed-time stability while effectively navigating dynamic environments and avoiding collisions.

The central problem addressed in this paper is the design of some behavioral functions that enables agents to achieve prescribed-time formation tracking under multi-task combinations, including collision avoidance. This problem is compounded by the inherent challenges of task conflicts, maintaining system stability, and ensuring bounded control inputs. To address these challenges, this paper proposes a novel control strategy that bases on null-space-based behavioral control and introduces switching mechanisms to achieve the desired objectives. The contributions of this paper are threefold as follow.

1) Two distinct behavior velocities using the time scale functions, is designed to realize the completion of sub-task goals within prescribed-time frames. This approach ensures that each sub-task is accomplished in a timely manner, contributing to the overall prescribed-time stability of the system.

2)We incorporate a gain switching mechanism into the formation velocity design, guaranteeing system stability when task conflicts. This mechanism allows the system to dynamically adjust its behavior in response to changing conditions, maintaining stability and performance.

3)Compared with [20–22], which are fixed-time frame works, a prescribed-time control strategy based on behavior projection of the null space is developed, facilitating formation tracking control with inter-agents collision avoidance.

The rest of the paper is organized as follows. Section II provides preliminary concepts and system description. In Section III, we first design two behavioral velocities capable of completing the sub-tasks at the prescribed time separately under the estimation of a set of observers, followed by designing a control strategy based on the null-space projection of the behaviors to complete the composite task in the prescribed time. Section IV provides simulation results in two-dimensional space to demonstrate the effectiveness of the proposed method. Finally, Section V concludes the paper.

Notation: I_n denote the n-dimension identity matrix. \mathbb{R}^n and $\mathbb{R}^{n\times n}$ are the sets of $n\times 1$ real vectors and $n\times n$ real matrix, respectively. $\|\cdot\|$ denotes the Euclidean norm. $\operatorname{sign}(\cdot)$ is the sign function of vector. For simplicity of presentation, the symbol (t) is omitted throughout this paper when there is no confusion, e.g., $p_i(t)$ is simplified as p_i .

II. PRELIMINARIES AND PROBLEM FORMULATION

A. Graph theory

We model the communication network of the N followers by a directed graph $\mathcal{G}=\{\mathcal{V},\mathcal{E}\}$, where $\mathcal{V}=\{1,\ldots,N\}$ denotes the set of nodes representing the N followers, $\mathcal{E}=\{(i,j)|i,j\in\mathcal{V}\}\subseteq N\times N$ stands for the set of edge. and $\mathcal{A}=[a_{ij}]\in\mathbb{R}^{N\times N}$ is the adjacency matrix representing the connection strength between followers, where $a_{ij}>0$ if $(j,i)\in\mathcal{E}$ and $a_{ij}=0$ otherwise. Moreover, we assumed that there are no self-loops, i.e., $a_{ii}=0$. \mathcal{G} has a directed spanning tree rooted at node k if there exists a node k such that all the

remaining nodes can access the signal of node k via a directed path. Define the in-degree matrix $\mathcal{D}:=\operatorname{diag}\left\{d_1,d_2,\ldots,d_n\right\}$ and the Laplacian matrix $\mathcal{L}=\mathcal{D}-\mathcal{A}$ as the degree matrix and Laplacian matrix of graph G, respectively, where $d_i=\sum_{j=1}^n a_{ij}$ for $i\in\mathcal{V}$. Besides, the auxiliary matrix $\mathcal{A}'=\operatorname{diag}\left\{a_{1(N+1)},a_{2(N+1)},\ldots,a_{N(N+1)}\right\}$ is introduced to present the communication connection between the leader and followers, where $a_{i(N+1)}>0$ if and only if the i-th follower can access leader's information directly.

Assumption 1. The directed graph G has a directed spanning tree rooted at the leader.

B. Problem formulation

Consider the first-order MAS containing N follower and one leader. The dynamic model of the follower i is

$$\dot{p}_i = u_i + \omega_i, i \in \mathcal{V} \tag{1}$$

where $p_i \in \mathbb{R}^n$, $u_i \in \mathbb{R}^n$ and ω_i are the position states, control input and disturbance of the follower i, respectively. n is the states' dimension and ω_i represents the uncertainty. We take n=2 in the following content. The leader, labeled as i=N+1, is described as follows:

$$\dot{p}_{N+1} = u_{N+1},\tag{2}$$

where $p_{N+1} \in \mathbb{R}^n$, $v_{N+1} \in \mathbb{R}^n$ and $u_{N+1} \in \mathbb{R}^n$ are the position, velocity states, control input of the leader, respectively.

Assumption 2. The disturbance of followers $\omega_i, \forall i \in \mathcal{V}$ and the input of leader u_{N+1} remains bounded with $\|\omega_i\| \leq \sigma_1, \forall i \in \mathcal{V}$ and $\|u_{N+1}\| \leq \sigma_2$, respectively.

To realize the prescribed-time formation, the following timevarying scale function is constructed:

$$\eta_l(t) = \begin{cases} \frac{(lT)^h}{(t_0 + lT - t)^h}, & t \in [t_0, t_0 + lT) \\ 1, & t \in [t_0 + lT, \infty) \end{cases}$$
(3)

where h>1, l is a positive integer, t_0 and T are initial time and pre-assigned constant, respectively. It can be found that $\frac{\dot{\eta}_l(t)}{\eta_l(t)}=\frac{h}{(t_0+lT-t)}$ for $t\in[t_0,t_0+lT)$, and $\frac{\dot{\eta}_l(t)}{\eta_l(t)}=0$ when $t\geq t_0+lT$. Meanwhile, $\eta_l^{-m}(t)(m>0)$ is monotonically decreasing on $[t_0,t_0+lT)$ with $\lim_{t\to t_0+lT^-}\eta_l^{-m}(t)=0$.

C. Lemma and definition

Lemma 1. [23] Under Assumption 1, there exists a matrix $P = diag\{p_1, ..., p_N\} > 0$ such that $Q = PH + H^TP$ is positive define, where $p_1, ..., p_N$ are determined by $[p_1, ..., p_N]^T = (H^T)^{-1}\mathbf{1}_N$, where $H = \mathcal{L} + \mathcal{A}'$.

Consider the following system

$$\dot{x}(t) = g(t, x(t)), x_{t_0} = t(t_0), \tag{4}$$

where $x(t) \in \mathbb{R}^n$ is the status, and $g : \mathbb{R}_{t_0} \times \mathbb{R}_n \to \mathbb{R}_n$ is a nonlinear function, $x(t_0)$ is the initial status.

Definition 1. [24] For system (4), as for a nonempty closed set S, if there exists a settling time function $T(x): \mathbb{R}^n \to T^*$

satisfying $x(t) \in \mathcal{S}, \forall t \geq T(x_0)$, where T^* is a positive constant that can be set arbitrarily and is not time-dependent, then the nonempty closed set S of system (4) is called prescribed-time stable.

Lemma 2. [25] For system (4), if there exists a Lyapunov function V(x) satisfying

$$e\dot{V}(x) \le -\left(c + k\frac{\dot{\eta}_l(t)}{\eta_l(t)}\right)V(x), t \in [t_0, t_0 + lT)$$

where η_l is defined in (3), $c \geq 0$ and k > 0 are constants. Then, we can obtain the solution as

$$\begin{cases} V(x) \le \eta_l^{-k}(t) e^{-c(t-t_0)} V(x_0), & t \in [t_0, t_0 + lT) \\ V(x) \equiv 0, t \in [t_0 + lT, \infty) \end{cases}$$

meaning that the origin of system (4) is globally prescribedtime stable with the prescribed-time $t_0 + lT$.

III. MAIN RESULTS

In practice, the condition that all follower acquire the leader state is demanding, and according to Assumption 1, the follower needs to effectively observe the leader state within a prescribed period of time. Therefore, the following distributed observation strategy is designed:

$$\dot{\hat{p}}_i = \alpha (c + \frac{\dot{\eta}_1}{\eta_1}) \zeta_{ip} - \gamma \text{sign}(\zeta_{ip}), \tag{5}$$

where $i \in \mathcal{V}$, $\zeta_{ip} = \sum_{j=1}^{N+1} a_{ij} (\hat{p}_i - \hat{p}_j)$. \hat{p}_i is observed states of leader in agent i, $\hat{p}_{N+1} = p_{N+1}$, c > 0, $\alpha \ge \frac{\lambda_{max}(P)}{\lambda_{max}(Q)}$ and $\gamma \ge \sigma_2$ are user-selectable parameters. $\eta_1(t)$ is defined in (3).

Lemma 3. [26] Under the observation of (5), and supposed that Assumption 1 and 2 holds, the followers in MAS described by (1) and (2) can estimate leader's states accurately within the prescribed time $T_{ob} = 2T$, i.e., $\lim_{t > t_0 + 2T} \hat{p}_i - p_{N+1} =$ $0, \forall i \in \mathcal{V}.$

In this paper, NSB methods are used so that agents can realize formation tracking under collision avoidance. First, two behavior velocities are designed to guarantee the prescribedtime formation and prescribed-time collision-avoidance. Then, the formation velocity is projected onto the obstacle avoidance velocity to form a desired velocity to ensure a prescribed time convergence under task conflict.

Before introduce collision avoidance behavior velocity, we assume that the size of follower i is represented by a circle with center p_i and radius r_i . We define the collision avoidance behavior function as

$$f_{io} = \begin{cases} Re^{\frac{R - \|p_i - p_i^*\|}{\|p_i - p_i^*\| - z_{ij}}}, & \underline{r}_{ij} < \|p_i - p_i^*\| \le R \\ R, & \text{otherwise} \end{cases}$$

where $R < \max \|\delta_i - \delta_j\|$, $\underline{r}_i = r_i + r_j$, δ_i is the offset from the follower i to the leader, p_i^* is the position of the nearest follower.

The collision avoidance behavior velocity is designed as

$$v_{io} = J_{io}^{\dagger} (c_{io} + k_{io} \frac{\dot{\eta}_2}{\eta_2}) \tilde{f}_{io} + k_{\omega} \operatorname{sign}(\tilde{f}_{io})$$
 (6)

where $c_{io} > 0$, $k_{io} > 1$, $k_{\omega} \geq \sigma_1$, $\tilde{f}_{io} = R - f_{io}$ is the collision avoidance behavior error for follower i and $J_{io}^{\dagger} =$ $J_{io}^{\mathrm{T}}(J_{io}J_{io}^{\mathrm{T}})^{-1}$ with

$$J_{io} = \frac{\partial f_{io}}{\partial p_i} = \begin{cases} -R\varphi_i \frac{(p_i - p_i^*)^\mathsf{T}}{\|p_i - p_i^*\|}, & \underline{r}_{ij} < \|p_i - p_i^*\| \le R\\ 0, & \text{otherwise} \end{cases}$$

$$\begin{split} \text{where } \varphi_i = e^{\frac{R - \|p_i - p_i^*\|}{\|p_i - p_i^*\| - c_{ij}}} \frac{R - \underline{c}_{ij}}{(\|p_i - p_i^*\| - \underline{c}_{ij})^2}. \end{split}$$
 The formation behavior velocity is designed as

$$v_{if} = \begin{cases} J_{if}^{\dagger} [\psi_{if1} \tilde{f}_{if} + \dot{\hat{p}}_{i}] + k_{\omega} \operatorname{sign}(\tilde{f}_{if}), & if J_{io} \equiv 0, \forall t \geq t_{0} \\ J_{if}^{\dagger} [\psi_{if2} \tilde{f}_{if} + \dot{\hat{p}}_{i}] + k_{\omega} \operatorname{sign}(\tilde{f}_{if}), & \text{otherwise} \end{cases}$$
(7)

where $\psi_{if1} = (c_{if} + k_{if} \frac{\dot{\eta}_2}{\eta_2}), \ \psi_{if2} = (c_{if} + k_{if} \frac{\dot{\eta}_3}{\eta_3}), \ c_{if} > 0,$ $k_{if} > 1$, k_{ω} is given in (6), $\tilde{f}_{if} = \hat{p}_i + \delta_i - p_i$, and $J_{if}^{\dagger} = J_{if}^{\mathrm{T}}(J_{if}J_{if}^{\mathrm{T}})^{-1}$ with

$$J_{if} = \frac{\partial p_i}{\partial p_i} = I_3.$$

With the null space projection between the formation tracking and collision avoidance behavior, the desired input for follower i is obtained by using (7) and (6) as

$$u_i = v_{io} + (I_n - J_{io}^{\dagger} J_{io}) v_{if}$$
 (8)

With the desired input design, the following theorem is derived.

Theorem 1. For systems (1), with the observer (5) and the the prescribed-time control protocol (8), the prescribedtime formation tracking with collision avoidance problem is completed within the prescribed time T=3T.

Proof. Define the following Lyapunov function candidate as:

$$V_i = \frac{1}{2} \gamma_{io} \tilde{f}_{io}^2 + \frac{1}{2} \gamma_{if} \tilde{f}_{if}^{\mathrm{T}} \tilde{f}_{if}$$
 (9)

where $\gamma_{if} > 0$ and $\gamma_{io} > 0$. Then, we prove in two case.

Case 1. If $||p_i - p_i^*|| > R, \forall t \ge t_0, i \in \mathcal{V}$ always holds.

We have $J_{io}^T J_{if} = 0, \forall t \geq t_0, i \in \mathcal{V}$. Then, the derivative of

$$\dot{V}_{i} = -\gamma_{io}\tilde{f}_{io}J_{io}u_{i} + \gamma_{if}\tilde{f}_{if}^{T}[\dot{p}_{i} - J_{if}(u_{i} + \omega_{i})]$$

$$= -\gamma_{if}(c_{if} + k_{if}\frac{\dot{\eta}_{2}}{\eta_{2}})\tilde{f}_{if}^{T}\tilde{f}_{if} - \gamma_{if}\tilde{f}_{if}^{T}[k_{\omega}\operatorname{sign}(\tilde{f}_{if}) - \omega_{i}]$$

$$\leq -\gamma_{if}(c_{if} + k_{if}\frac{\dot{\eta}_{2}}{\eta_{2}})\tilde{f}_{if}^{T}\tilde{f}_{if}$$

$$\leq -2(c_{if} + k_{if}\frac{\dot{\eta}_{2}}{\eta_{2}})V_{i}, \tag{10}$$

where J_{io}^{\dagger} and $k_{\omega} > \sigma_1$ applied. With Lemma 2, we have $||p_i |p_{N+1} - \delta_i|| \equiv 0, \forall t \geq t + 2T \text{ under } R > \max ||\delta_i - \delta_i||$ and $\hat{p}_i = p_{N+1}, \forall t \geq t_0 + T$ for all followers, and collision don't happen since $||p_i - p_i^*|| > R, \forall t \geq t_0, i \in \mathcal{V}$. Then, we consider the boundedness of input $u_i,\ u_i=v_{io}+(I_n-J_{io}^\dagger J_{io})v_{if}=v_{if}=(c_{if}+k_{if}\frac{h}{2T}\eta_2)\eta_2^{-k_{if}}e^{-c_{if}(t-t_0)}\tilde{f}_{if}(t_0)+\dot{\hat{p}}_i$ is bounded with the boundedness of $(c_{if}+k_{if}\frac{h}{2T}\eta_2)\eta_2^{-k_{if}}$ and $\dot{\hat{p}}_i$.

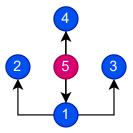


Fig. 1: Communication graph topology.

Case 2. the tasks are conflicting, i.e., there exist a moment $t^* < t_0 + 2T$ satisfying $||p_i(t^*) - p_i^*(t^*)|| \le R$, we divide the proof into two steps.

Step 1.
$$\forall t \in [t_0, t_0 + 2T)$$

We refined V_i as $V_i = \frac{1}{2}\gamma_{io}\tilde{f}_{io}^2$ since the collision avoidance is more urgent than formation tracking, and (10) becomes

$$\dot{V}_{i} = -\gamma_{io}\tilde{f}_{io}J_{io}(u_{i} + \omega_{i})$$

$$= -\gamma_{io}\tilde{f}_{io}J_{io}(v_{io} + \omega_{i})$$

$$\leq -\gamma_{io}(c_{io} + k_{io}\frac{\dot{\eta}_{2}}{\eta_{2}})\tilde{f}_{io}^{2}$$

$$\leq -2(c_{io} + k_{io}\frac{\dot{\eta}_{2}}{\eta_{2}})V_{i},$$

where $J_{io}(I_n - J_{io}^{\dagger}J_{io}) = 0$ is applied. With Lemma 2, we have $\|p_i - p_i^*\| \equiv 0, \forall t \geq t_0 + 2T$, and $u_i = J_{if}^{\dagger}(c_{io} + k_{io}\frac{\dot{\eta}_2}{\eta_2})\tilde{f}_{io} + (I_n - J_{io}^{\dagger}J_{io})[(c_if + k_{if}\frac{\dot{\eta}_3}{\eta_3})\tilde{f}_{if} + \dot{p}_i] \leq J_{if}^*(c_{io} + k_{io}\frac{h}{2T}\eta_2)\eta_2^{-k_{io}}e^{-c_{io}(t-t^*)}\tilde{f}_{if}(t^*) + (I_n - J_{io}^{\dagger}J_{io})[(c_if + k_{if}\frac{\dot{\eta}_3}{\eta_3})(\tilde{f}_{if}(t^*) + R - \underline{r}_i) + \dot{p}_i]$ is boundedness. Step 2. $\forall t \geq t_0 + 2T$ When the conflict is over, we have $t \geq t_0 + 2T$, V_i is redesigned as (9), (10) becomes

$$\dot{V}_i \le -(c_{if} + k_{if} \frac{\dot{\eta}_3}{\eta_3}) V_i.$$

According to Lemma 2 and 3, we have the formation tracking is realized within the prescribed time T=3T. The analysis of the boundedness of u_i is similar to the Case~1. Thus, we have u_i is bounded $\forall t \geq t_0$.

IV. SIMULATION

This section provides a simulation example to verify the validity of the theoretical results. We consider a directed communication multi-agent system with four followers (indexed from 1 to 4) and a leader (indexed at 5), whose directed communication graph consists of a minimum spanning tree rooted at the leader, as shown in Fig. 1.

Each follower and the leader are modeled by (1) and (2), respectively. The disturbance of follower i is set as $\omega_i = [\sin(t), \cos(t)]$ and the leader's input is set as $u_0 = [5\sin(\frac{\pi t}{3}), 5\cos(t\frac{\pi t}{3})]^{\mathrm{T}}$. The initial states and the offset from the follower to the leader of agents are

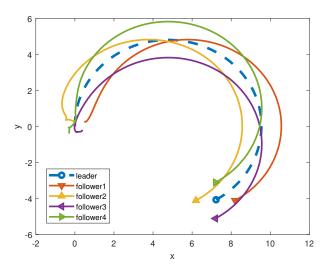


Fig. 2: Formation trajectories.

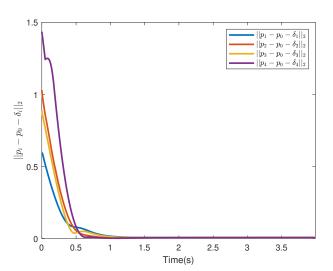


Fig. 3: Formation tracking errors $||p_i - p_0 - \delta_i||$.

$$\begin{cases} p_0(0) = [0, 0]^T \\ p_1(0) = [0.5, 0.3]^T \\ p_2(0) = [0, 0.3]^T \\ p_3(0) = [0.4, -0.2]]^T \\ p_4(0) = [-0.3, -0.4]^T, \end{cases} \begin{cases} \delta_1 = [1, 0]^T \\ \delta_2 = [-1, 0]^T \\ \delta_3 = [0, -1]^T \\ \delta_4 = [0, 1]^T. \end{cases}$$

The design parameters of the proposed algorithm in (5)-(8) are selected as $t_0=0s$, $\alpha=13$, c=1.3, T=1s, $\gamma=3$, $c_{io}=1.8$, $k_{io}=2.5$, R=0.5, $r_i=0.1$, $k_{\omega}=2$, $c_{if}=4.2$ and $k_{if}=3$.

The simulation results are presented in Figs. 2-5. As can be seen in Fig. 2, the followers tracked the leader forming a square for cruising. Fig. 3 shows the formation tracking errors of followers, which verifies the formation tracking errors converged to zero within the prescribed time $t_0 + 3T = 3s$. The control inputs are illustrated in Fig. 4, we can find that

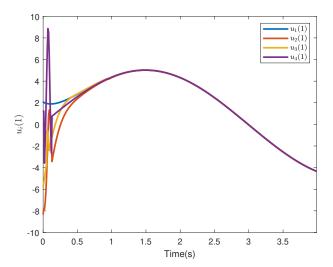


Fig. 4: Control inputs $u_i(t)$.

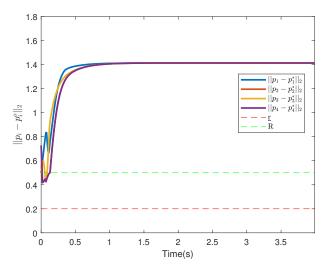


Fig. 5: Distances between agents and obstacles.

the inputs are bounded throughout the time interval, and they track the velocity of leader u_0 within a prescribed time. Fig. 5 depicts the distances between followers, verifying the distances between followers are always greater than \underline{r} . All the above results demonstrate the effectiveness of the control algorithm (8).

V. CONCLUSION

In this paper, we study the problem of prescribed-time formation tracking with collision avoidance for first-order multi-intelligent body networks with directed graphs. Based on the idea of behavioral control, two behaviors are designed to guarantee the predefined time formation and predefined time collision avoidance, respectively, and a control algorithm based on the null-space projection of the behaviors is proposed to successfully solve the formation tracking problem with collision avoidance. The stability of the closed-loop system is proved by constructing a new set of Lyapunov functions.

The effectiveness of the proposed algorithm is verified by simulation examples.

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