Letter

Adaptive Consensus of Uncertain Multi-Agent Systems With Unified Prescribed Performance

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Dear Editor,

An adaptive consensus control algorithm for uncertain multi-agent systems (MAS), capable of guaranteeing unified prescribed performance, is presented in this letter. Unlike many existing prescribed performance related works, the developed control exhibits some features. Firstly, a distributed prescribed time observer is introduced so that not only each follower is able to estimate the leader's signal within a predetermined time, but also the control design for each agent is independent with its neighbors, making the original coupled relationship between agents removed. Secondly, by constructing some nonlinear transformations and parameter-oriented asymmetric barrier function, the problem of ensuring different kinds of prescribed performance behaviors can be converted into the selection of design parameters, making the control redesign not needed and different mission requirements satisfied under a fixed control framework. According to the Lyapunov method, it is shown that not only the closed-loop signals are bounded, but also the consensus errors can be evolved within the prescribed boundaries. Simulations are provided to verify the effectiveness of the proposed approach.

Distributed control of multi-agent systems has been a hot research topic at the forefront of the control community in recent decades, with related studies spanning various interdisciplinary areas such as consensus [1], [2], distributed optimization [3], formation control [4], and evolutionary games [5]. Among them, consensus, whose aim is to achieve state agreement by using local information, is always a fundamental research topic in control theory and applications [6]–[8]. The existing works can be mainly divided into two categories, namely leader-following consensus control and leaderless consensus control, depending on the presence or absence of a (virtual) leader. In particular, the leader-following consensus control is widely studied due to its simplicity and high scalability [9].

Guaranteeing the predefined transient and steady-state specifications is crucial for the distributed consensus control of leader-following MAS. In this context, prescribed performance control (PPC) offers a straightforward and constructive methodology, in which the transient behavior of the closed-loop system is predetermined through user-defined performance constraints [10]. Subsequently, PPC has been utilized for the consensus problem of MAS [11], [12]. Unfortunately, for the most existing PPC-based results, an implicit condition on the initial tracking error must be satisfied, i.e., there exists a hard constraint on the initial error. Consequently, the users have to re-select the initial value of performance boundary and then judge the constraining condition when the system is interrupted or restarted, resulting in the controller implementation more complex and less friendly. Inspired by our previous work in [13], Li *et al*. [14] achieved global consensus tracking for parametric MAS so that the requirement on initial conditions is removed. Nevertheless, the control strategy in [14] only ensures the global performance and other different task-specific performance constraints in real applications are not involved. If the users would like to guarantee other different performance behaviors, one has to redesign controller and reanalyze the stability of the closed-loop system, resulting in the control implementation more complex and less friendly.

Motivated by the above observations, in this letter, an adaptive unified consensus performance control scheme is proposed for a class of uncertain nonlinear MAS. Different from the normally considered finite-time observer, by utilizing the prescribed time observer borrowed from [15], each follower employs the output of the observer (rather than the leader signal) as their local reference signal, elegantly circumventing the difficulties associated with the signal coupling in control design and stability analysis. Furthermore, by constructing some novel nonlinear transformations, the problem of guaranteeing different consensus error performance constraints in a unified manner can be converted into the selection of design parameters, making the control redesign and stability reanalysis not required.

Preliminary and problem formulation: Consider a MAS that is composed of $N+1$ agents with N follower agents and one leader agent, where $N \geq 1$. The set of followers and leaders are represented by $\mathcal{V}_f = \{1,\ldots,N\}$ and $\mathcal{V}_l = \{0\}$, respectively. The communication topology among the followers and the leader is described by a directed graph $\mathcal{G} = (\mathcal{V},\mathcal{E})$, where $\mathcal{V} = \mathcal{V}_f + \mathcal{V}_l$ is the set of vertices representing $N+1$ agents, and $\mathcal{E} \subseteq \mathcal{V}\times\mathcal{V}$ denotes the edge set. $\mathcal{N}_i = \{j \in \mathcal{V} | (j,i) \in \mathcal{E}\}$ stands for the set of the neighbors of agent i, in other words, agent i can receive information from agent j. $\mathcal{A} = [a_{ij}] \in \mathbb{R}^{(N+1)\times(N+1)}$ is the adjacency matrix, where $(j,i) \in \mathcal{E} \Leftrightarrow a_{ij} > 0$, otherwise, $a_{ij} = 0$. The degree matrix D is defined by $D = \mathrm{diag}\{D_i\} \in \mathbb{R}^{(N+1)\times(N+1)}$ with $D_i = \sum_{j\in\mathcal{N}_i} a_{ij}$, and $L = D-\mathcal{A}$ represents the Laplacian matrix of $\mathcal{G}$.

For agent $i \in \mathcal{V}_f$, the nonlinear dynamic is indicated as

$$\dot{x}_i = u_i + f_i(p_i, x_i) \tag{1}$$

where $x_i \in \mathbb{R}^m$ is the state; $u_i \in \mathbb{R}^m$ is the control input; $p_i \in \mathbb{R}^r$ denotes an unknown parameter vector, and $f_i \in \mathbb{R}^m$ represents the system uncertainty including modeling error and external disturbance, which is not necessarily identical.

The dynamics of the leader is given as $\dot{x}_0 = f_0(x_0)$ with $x_0 \in \mathbb{R}^m$ being the bounded system state and $f_0(x_0) \in \mathbb{R}^m$ being bounded and piecewise continuous w.r.t. t. For convenience, here we take $m = 1$.

Our goal in this letter is to develop a distributed robust adaptive controller for system (1) so that:

O_1: All signals in the closed loop systems are bounded; and

O_2: Different kinds of prescribed consensus tracking error performance can be guaranteed in a unified control framework without control redesign.

To this end, the following assumptions are imposed.

Assumption 1: The topology among the followers and the leader contains a directed spanning tree, where the leader acts as the root.

Assumption 2: For the uncertain function $f_i(p_i, x_i)$, there exist an unknown constant $\theta_i \geq 0$ and a known smooth function $\phi_i(x_i) \geq 0$ so that $\|f_i(p_i, x_i)\| \leq \theta_i\phi_i(x_i)$. If x_i is bounded, so are ϕ_i and f_i.

Main results:

Distributed prescribed-time observer: Since only a subset of the follower agents is able to receive information from the leader, a distributed prescribed time observer is required to estimate the leader state x_0 in finite time. Inspired by [15], our observer design evolves a time-dependent scaling function: $\rho(t) = \frac{T^h}{(T-t)^h}$ for $t \in [0,T)$, and $\rho(t) = 1$ for $t \in [T,\infty)$, where $h > 1$, and $T > 0$ denotes the prescribed convergence time of observer. Let $\hat{x}_i$ be the observation value of x_0 given by agent i, the distributed prescribed-time observer is designed as

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$$\dot{\hat{x}}_i = \frac{1}{\sum_{j=0}^{N+1} a_{ij}} \sum_{j=0}^{N+1} a_{ij}\dot{\hat{x}}_j - \frac{\gamma + \frac{\dot{\rho}}{\rho}}{\sum_{j=0}^{N+1} a_{ij}} \sum_{j=0}^{N+1} a_{ij}\left(\hat{x}_i - \hat{x}_j\right) \tag{2}$$

for $i \in \mathcal{V}_f$, where $\hat{x}_0 = x_0$, and $\gamma > 0$ is a user-chosen parameter. The observation error is denoted by $\tilde{x}_i = \hat{x}_i - x_0$. Note that $\sum_{j=0}^{N+1} a_{ij} \neq 0$ under Assumption 1, then (2) is well-defined.

Lemma 1 [15]: If Assumption 1 holds, the distributed observer (2) can estimate the leader's state and at the same time the estimation deviation $\tilde{x}_i$ for $i \in \mathcal{V}_f$, converges to 0 within a prescribed time T.

Prescribed performance function: For the ith follower, define the consensus tracking error as $e_i(t) = x_i(t) - \hat{x}_i(t)$. To guarantee the consensus error performance constraint, inspired by our previous work [13], [16] the performance function is constructed as

$$\Psi_i(\beta_i(t)) = \frac{\tau_i\beta_i(t)}{\sqrt{1-\beta_i^2(t)}}, \ i \in \mathcal{V}_f \tag{3}$$

where $\tau_i > 0$, and $\beta_i(t)$ denotes the rate function: $\beta_i(t) = (\beta_{i0} - \beta_{if})\times \exp(-\sigma_i t) + \beta_{if}$, with $0 < \beta_{if} < \beta_{i0} \leq 1$, and $\sigma_i > 0$. In addition, according to (3) and the definition of $\beta_i(t)$, it is not difficult to prove that Ψ_i is strictly monotonic increasing w.r.t. β_i.

Upon utilizing the performance function (3), the objective O_2 in terms of consensus error $e_i(t)$ can be stated mathematically as

$$\Psi_i(-\underline{\delta}_i\beta_i(t)) < e_i(t) < \Psi_i(\overline{\delta}_i\beta_i(t)), \quad i \in \mathcal{V}_f \tag{4}$$

$$\Psi_i(\overline{\delta}_i\beta_i) = \frac{\tau_i\overline{\delta}_i\beta_i}{\sqrt{1-(\overline{\delta}_i\beta_i)^2}}, \quad \Psi_i(-\underline{\delta}_i\beta_i) = \frac{-\tau_i\underline{\delta}_i\beta_i}{\sqrt{1-(\underline{\delta}_i\beta_i)^2}} \tag{5}$$

where $0 < \underline{\delta}_i, \overline{\delta}_i \leq 1$ are user-chosen parameters.

Here, it is shown from (4) and (5) that, by choosing different design parameters β_{i0}, $\underline{\delta}_i$, and $\overline{\delta}_i$, different performance behaviors can be ensured in a unified framework.

Case 1: If $\overline{\delta}_i$, $\underline{\delta}_i$, and β_{i0} are chosen as $\overline{\delta}_i = \underline{\delta}_i = \beta_{i0} = 1$, it is seen from (5) that $\Psi_i(\overline{\delta}_i\beta_{i0}) = \infty$ and $\Psi_i(-\underline{\delta}_i\beta_{i0}) = -\infty$, which implies that there are no upper/lower constraints on initial error and the corresponding control is a global result;

Case 2: If $\overline{\delta}_i = \beta_{i0} = 1$ and $0 < \underline{\delta}_i < 1$, one has $\Psi_i(-\underline{\delta}_i\beta_{i0}) = -\underline{\epsilon}_i < 0$, and $\Psi_i(\overline{\delta}_i\beta_{i0}) = \infty$ with $\underline{\epsilon}_i$ being a positive and bounded constant, then there is a lower constraint and no upper constraint on initial data, which belongs to an asymmetric result and is applicable to any scenario with $\text{sign}(e_i(0)) = 1$;

Case 3: If $\underline{\delta}_i = \beta_{i0} = 1$ and $0 < \overline{\delta}_i < 1$, one has $\Psi_i(\overline{\delta}_i\beta_{i0}) = \overline{\epsilon}_i > 0$ and $\Psi_i(-\underline{\delta}_i\beta_{i0}) = -\infty$, with $\overline{\epsilon}_i$ being a positive and bounded constant, then there is an upper constraint and no lower constraint on initial data, which is also an asymmetric result and is applicable to any case with $\text{sign}(e_i(0)) = -1$;

Case 4: If $0 < \overline{\delta}_i\beta_{i0} < 1$ and $0 < \underline{\delta}_i\beta_{i0} < 1$, the initial error is required to satisfy $\Psi_i(-\underline{\delta}_i\beta_{i0}) = -\underline{\epsilon}_i < e_i(0) < \Psi_i(\overline{\delta}_i\beta_{i0}) = \overline{\epsilon}_i > 0$, then there exist lower/upper constraints on initial error simultaneously, which is a semi-global yet asymmetric result.

The developed control offers a novel systematic framework for MAS to achieve uniform global and asymmetric semi-global prescribed tracking performance. To accomplish the prescribed performance control objective for uncertain MAS, we employ a nonlinear mapping $\mathcal{M}: (-\underline{\delta}_i, \overline{\delta}_i) \to (-\infty, \infty)$ with $\mathcal{M}(0) = 0$,

$$\varepsilon_i(t) \triangleq \mathcal{M}(\zeta_i(t)) = \frac{\zeta_i(t)}{(\underline{\delta}_i + \zeta_i)(\overline{\delta}_i - \zeta_i)}, \ i \in \mathcal{V}_f$$

$$\zeta_i(t) \triangleq \frac{\eta_i(t)}{\beta_i(t)}, \ \eta_i(t) \triangleq \frac{e_i(t)}{\sqrt{e_i^2(t) + \tau_i^2}} \tag{6}$$

with ζ_i denoting the modulated error and η_i being the normalized error. Moreover, the following property can be easily derived from the aforementioned transformation.

Property 1: If $\zeta_i(0)$ satisfies $-\underline{\delta}_i < \zeta_i(0) < \overline{\delta}_i$ and $\varepsilon_i(t)$ is bounded for $\forall t \geq 0$, then there exist some constraints $\underline{\delta}_{1i}$ and $\overline{\delta}_{1i}$ so that $-\underline{\delta}_i < -\underline{\delta}_{1i} \leq \zeta_i(t) \leq \overline{\delta}_{1i} < \overline{\delta}_i$.

Controller design: The time derivative of ε_i as defined in (6) is

$$\dot{\varepsilon}_i = \frac{\partial\mathcal{M}(\zeta_i)}{\partial\zeta_i}\frac{d\zeta_i}{dt} = \mu_i\left(\frac{r_i}{\beta_i}\dot{e}_i - \frac{\dot{\beta}_i}{\beta_i^2}\eta_i\right) = \varrho_i\dot{e}_i + d_i \tag{7}$$

where $\mu_i = \frac{\underline{\delta}_i\overline{\delta}_i + \zeta_i^2}{(\underline{\delta}_i + \zeta_i)^2(\overline{\delta}_i - \zeta_i)^2}$, $r_i = \frac{\tau_i^2}{\sqrt{e_i^2 + \tau_i^2(e_i^2 + \tau_i^2)}}$, $\varrho_i = \frac{\mu_i r_i}{\beta_i}$, and $d_i = -\frac{\mu_i\dot{\beta}_i}{\beta_i^2}\eta_i$ are available for control design.

The derivative of quadratic function $V_1(t) = \frac{1}{2}\sum_{i=1}^N \varepsilon_i^2$ yields

$$\dot{V}_1 = \sum_{i=1}^N \left[\varepsilon_i\left(\varrho_i(u_i - \dot{\hat{x}}_i)\right) + \varepsilon_i\varrho_i f_i(x_i) + \varepsilon_i d_i\right]. \tag{8}$$

By using Young's inequality, together with Assumption 2, one has

$$\varepsilon_i\varrho_i f_i(x_i) \leq \theta_i^2\varepsilon_i^2\varrho_i^2\phi_i^2 + \frac{1}{4}, \ \ \varepsilon_i d_i \leq \varepsilon_i^2 d_i^2 + \frac{1}{4}.$$

Therefore, the term $\varepsilon_i\varrho_i f_i(x_i) + \varepsilon_i d_i$ can be upper bounded by

$$\varepsilon_i\varrho_i f_i(x_i) + \varepsilon_i d_i \leq b_i\varepsilon_i^2\varphi_i + \frac{1}{2}$$

with $b_i = \max\{\theta_i^2, 1\} > 0$ being an unknown parameter, and $\varphi_i = \varrho_i^2\phi_i^2 + d_i^2 \geq 0$ denoting a computational function. Then (8) becomes

$$\dot{V}_1 \leq \sum_{i=1}^N \left[\varepsilon_i\left(\varrho_i(u_i - \dot{\hat{x}}_i)\right) + b_i\varepsilon_i^2\varphi_i + \frac{1}{2}\right]. \tag{9}$$

Designing the distributed adaptive controller as

$$u_i = -\frac{1}{\varrho_i}(c_i + \hat{b}_i\varphi_i)\varepsilon_i + \dot{\hat{x}}_i \tag{10a}$$

$$\dot{\hat{b}}_i = \xi_i\varepsilon_i^2\varphi_i - k_i\hat{b}_i, \ \ \hat{b}_i(0) \geq 0 \tag{10b}$$

where $c_i > 0$, $\xi_i > 0$, and $k_i > 0$, $\hat{b}_i$ is the parameter estimate of b_i, and $\hat{b}_i(0)$ is the initial value of parameter estimate. Furthermore, it is shown that $\hat{b}_i(t) \geq 0$ holds for all $t \geq 0$, with the conditions $\hat{b}_i(0) \geq 0$ and $\xi_i\varepsilon_i^2\varphi_i \geq 0$.

Theorem 1: Under Assumptions 1 and 2, applying the distributed control law (10) to the uncertain MAS (1) achieves objectives $O_1 - O_2$.

Proof: Substituting the controller (10) into $s_i\varrho_i(u_i - \dot{\hat{x}}_i)$, we have

$$\varepsilon_i\varrho_i(u_i - \dot{\hat{x}}_i) = -c_i\varepsilon_i^2 - \hat{b}_i\varphi_i\varepsilon_i^2. \tag{11}$$

Constructing the Lyapunov function candidate as $V(t) = V_1(t) + \sum_{i=1}^N \frac{1}{2\xi_i}\tilde{b}_i^2$, where $\tilde{b}_i = b_i - \hat{b}_i$ is the estimate error. With the aid of (9) and (11), the derivative of $V(t)$ is

$$\dot{V} \leq \sum_{i=1}^N \left[-c_i\varepsilon_i^2 + \tilde{b}_i\varepsilon_i^2\varphi_i + \frac{1}{2} - \frac{1}{\xi_i}\tilde{b}_i\dot{\hat{b}}_i\right]. \tag{12}$$

Substituting the adaptive law as given in (10) into (12), one has

$$\dot{V} \leq \sum_{i=1}^N \left[-c_i\varepsilon_i^2 + \frac{k_i}{\xi_i}\tilde{b}_i\hat{b}_i + \frac{1}{2}\right]. \tag{13}$$

As $\frac{k_i}{\xi_i}\tilde{b}_i\hat{b}_i = \frac{k_i}{\xi_i}\tilde{b}_i(b_i - \tilde{b}_i) \leq \frac{k_i}{2\xi_i}(b_i^2 - \tilde{b}_i^2)$, then (13) can be rewritten as

$$\dot{V} \leq \sum_{i=1}^N \left[-c_i\varepsilon_i^2 - \frac{k_i}{2\xi_i}\tilde{b}_i^2 + \frac{k_i}{2\xi_i}b_i^2 + \frac{1}{2}\right] \leq -\Upsilon_1 V + \Upsilon_2 \tag{14}$$

where $\Upsilon_1 = \min\{2c_1, k_1, \ldots, 2c_N, k_N\} > 0$, $\Upsilon_2 = \sum_{i=1}^N(\frac{k_i}{2\xi_i}b_i^2 + \frac{1}{2}) > 0$.

According to (14), $V \in L_\infty$, thus $\varepsilon_i \in L_\infty$ and $\tilde{b}_i \in L_\infty$, which further indicates that $\hat{b}_i \in L_\infty$. According to the Property 1, if $-\underline{\delta}_i < \zeta_i(0) < \overline{\delta}_i$, $-1 \leq -\underline{\delta}_i < -\underline{\delta}_{1i} \leq \zeta_i(t) \leq \overline{\delta}_{1i} < \overline{\delta}_i \leq 1$ holds for $\forall t \geq 0$. Since $\zeta_i = \frac{\eta_i}{\beta_i}$ and $0 < \beta_{if} \leq \beta_i(t) \leq \beta_{i0} \leq 1$, there exist some constants $\underline{\eta}_i$ and $\overline{\eta}_i$ such that $-1 < -\underline{\eta}_i < -\underline{\eta}_{1i} \leq \eta_i(t) \leq \overline{\eta}_{1i} < \overline{\eta}_i < 1$. Furthermore, $e_i \in L_\infty$. This implies that x_i, $f_i(x_i)$, ϕ_i, and φ_i are bounded as well. From (10), it can be observed that u_i and $\hat{b}_i$ are also bounded. Based on the above analysis, as $\varepsilon_i(t)$ is bounded, then $e_i(t)$ is guaranteed to stay within the prescribed performance region, which implies that (4) is satisfied. ■

Numerical example: Consider a group of 4 follower agents and one leader agent, where $f_i = p_{i1}x_i^2 + \sin(p_{i2}x_i)$ with $p_i = [p_{i1}, p_{i2}]^T = [2, 0.3]^T$ for $i = 1,2,3$, $f_4 = p_{41}x_4\sin(x_4) + \exp(p_{42}x_4^2)$ with $p_4 = [p_{41}, p_{42}]^T = [3,-1]^T$, and $\dot{x}_0 = -1/4\cos(t/2)$ with $x_0(0) = 1$. The topology among the agents is given in Fig. 1(a), which satisfies Assumption 1. We select $T = 2$, $h = 3$, $\gamma = 0.3$, $\hat{b}_i(0) = 0$, and $[\hat{x}_1(0), \hat{x}_2(0), \hat{x}_3(0), \hat{x}_4(0)]^T = [0.6, 1.2, 0.8, 1.4]^T$. The design parameters are $c_i = 5$, $k_i = 1$, $\xi_i = 0.001$, and $\tau_i = 1$. To facilitate the description in simulation, we choose the identical performance function Ψ_i for each agent, i.e., $\Psi_i(\bar{\delta}_i\beta_i) = \Psi(\bar{\delta}\beta)$ with $\beta(t) = (\beta_0 - \beta_f)\exp(-2t) + \beta_f$ with $\beta_f = 0.1$.

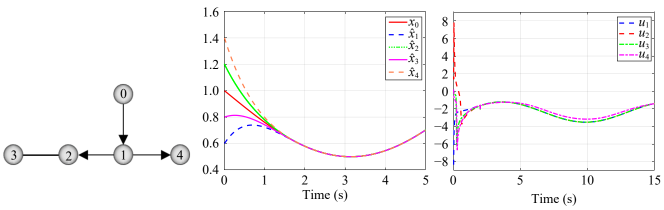

Fig. 1. The communication topology and trajectories of $\hat{x}_i$, x_0, and u_i. (a) The interactions among the agents; (b) The responses of $\hat{x}_i$ and x_0; (c) Evolutions of control inputs u_i.

Firstly, we verify that the algorithm can achieve global performance (i.e., Case 1). Choose $\underline{\delta} = \bar{\delta} = \beta_0 = 1$, thus $\Psi(-\underline{\delta}\beta_0) = -\infty$ and $\Psi(\bar{\delta}\beta_0) = +\infty$. The initial states of the 4 followers are given as $x(0) = [x_1(0), x_2(0), x_3(0), x_4(0)]^T = [1.2, -0.2, 1, 1.3]^T$. The trajectories of observers and control inputs are plotted in Figs. 1(b) and 1(c), from which it is seen that the state estimates and control inputs remain bounded for all time. Meanwhile, the trajectories of consensus errors are plotted in Fig. 2(a), which shows that the errors are always within the pregiven regions, regardless of the initial tracking errors of each agent. Furthermore, in order to show that the developed algorithm can also achieve other performance behavior with identical control in Case 1, we consider here Cases 2 and 3 with respect to the asymmetric prescribed tracking performance. The initial states of the 4 followers are given as $x(0) = [0.8, 1.3, 2, 1.5]^T$ and $x(0) = [0.2, 1, -0.5, 0.8]^T$. Choose $\underline{\delta} = 0.8$, $\bar{\delta} = \beta_0 = 1$ and $\bar{\delta} = 0.8$, $\underline{\delta} = \beta_0 = 1$ respectively. Figs. 2(b) and 2(c) illustrate the tracking error responses, which indicates that the tracking errors are always within the predetermined regions.

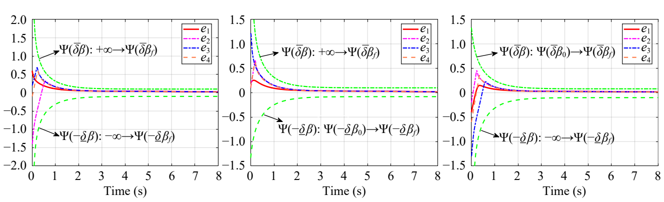

Fig. 2. Prescribed behavior of tracking errors e_i in different cases. (a) The evolutions of e_i in Case 1; (b) The evolutions of e_i in Case 2; (c) The evolutions of e_i in Case 3.

Conclusion: This letter has investigated the unified performance consensus tracking problem of uncertain MAS. The advantage of this work lies in its ability to fulfill diverse task-specific performance requirements only by selecting design parameters, making the control redesign and stability reanalysis not required.

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