Observer-based Control of Multi-agent Systems under STL Specifications ★

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Abstract: This paper proposes a decentralized controller for large-scale heterogeneous multi-agent systems subject to bounded external disturbances, where agents must satisfy Signal Temporal Logic (STL) specifications requiring cooperation among non-communicating agents. To address the lack of direct communication, we employ a decentralized k-hop Prescribed Performance State Observer (k-hop PPSO) to provide each agent with state estimates of those agents it cannot communicate with. By leveraging the performance bounds on the state estimation errors guaranteed by the k-hop PPSO, we first modify the space robustness of the STL tasks to account for these errors, and then exploit the modified robustness to design a decentralized continuous-time feedback controller that ensures satisfaction of the STL tasks even under worst-case estimation errors. A simulation result is provided to validate the proposed framework.

Keywords: Multi-agent systems, Signal Temporal Logic, Observer-based control, Task/communication graphs mismatch, Decentralized control and estimation.

1. INTRODUCTION

A multi-agent system (MAS) consists of a collection of interacting agents that collaborate or compete to accomplish specific objectives. Distributing control among agents enhances the scalability, flexibility, and resilience, enabling effective operation in complex, dynamic environments where single-agent systems are limited. Owing to these advantages, considerable research efforts have focused on the control of MAS for tasks such as formation control (Oh et al., 2015), consensus (Olfati-Saber et al., 2007), and flocking (Olfati-Saber, 2006).

In recent years, the control of MAS has been further extended to handle more complex specifications expressed through temporal logics (Maler and Nickovic, 2004). In particular, several studies have explored the use of Signal Temporal Logic (STL) to formally specify and guarantee high-level tasks in multi-agent coordination (Lindemann and Dimarogonas, 2021; Liu et al., 2025) and planning (Buyukkocak et al., 2021; Sun et al., 2022). However, these control methods heavily rely on the existence of communication links among the agents that must cooperate, limiting their applicability in scenarios where collaboration is required despite the absence of direct communication. To address this limitation, Marchesini et al. (2025) proposes a task decomposition algorithm that redefines tasks involving non-communicating agents to align them with the available communication topology. Nevertheless, this approach requires solving an optimization problem to decompose the task along a selected path, introducing an additional layer of complexity to the control problem and creating a dependency on the chosen path.

For this reason, in this paper we extend our previous works on k-hop observer-based control for MAS (Zaccherini et al., 2025a,c) to handle STL specifications. By leveraging the decentralized k-hop Prescribed Performance State Observer (k-hop PPSO) developed in Zaccherini et al. (2025c), each agent can estimate the states of the non-communicating agents with which it must collaborate, while ensuring that the predefined performance bounds specified at the design stage are satisfied. Based on the performance guarantees provided by the k-hop PPSO on the state estimation errors, the space robustness (Donzé and Maler, 2010) of the STL tasks involving non-communicating agents is adjusted to account for the worst-case estimation errors. Then, a decentralized Prescribed Performance Controller (PPC) (Bechlioulis and Rovithakis, 2008) based on the modified robustness is proposed to ensure satisfaction of the task even when the non-local information is replaced by estimates.

The remainder of the paper is organized as follows. Section 2 presents the preliminaries and the problem formulation. Section 3 introduces the adjustment for the space robustness of the STL tasks to account for the state estimation errors. Section 4 presents the proposed observer-based decentralized controller. Section 5 shows a case study. Section 6 concludes the paper with future work directions.

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2. PRELIMINARIES AND PROBLEM SETTING

Notation: We denote by $\mathbb{R}$, $\mathbb{R}_{\geq 0}$, and $\mathbb{R}_{>0}$ the sets of real, non-negative and positive real numbers, respectively. Let $|S|$, S^c, and ∂S be the cardinality, complement and boundary of a set S. Given N sets $\{S_1, \ldots, S_N\}$, we denote their Cartesian product, intersection, and union by $\bigtimes_{i=1}^{N} S_i$, $\bigcap_{i=1}^{N} S_i$, and $\bigcup_{i=1}^{N} S_i$, respectively. For a set $S = \{s_1, \ldots, s_n\}$, $\max_{i\in\{1,\ldots,n\}}\{s_i\}$ denotes its maximum element. We use $\top$ and $\bot$ to denote the logical values true and false. Given a symmetric matrix $B \in \mathbb{R}^{n\times n}$, $B \succ 0$ indicates that B is positive definite. For $x \in \mathbb{R}^n$, $\|x\| = \sqrt{x^\top x}$. We use $f \in \mathcal{C}_1$ to indicate that a function f is continuously differentiable in its domain. For $a \in \mathbb{R}$, $\exp(a) := e^a$. The diagonal matrix with diagonal entries $a_1, \ldots, a_n$ is denoted by $\mathrm{diag}(a_1, \ldots, a_n)$.

2.1 Signal Temporal Logic (STL)

Signal Temporal Logic (STL) is a formalism for specifying temporal and quantitative properties of continuous-time signals (Maler and Nickovic, 2004). It combines logical predicates with temporal operators to encode constraints on both signal values and time intervals over which they must hold. Each predicate μ is defined by a continuously differentiable function $\mathcal{P} : \mathbb{R}^n \to \mathbb{R}$, such that $\mu = \top$ if $\mathcal{P}(x) \geq 0$ and $\mu = \bot$ otherwise, for $x \in \mathbb{R}^n$. In this paper we consider non-temporal (1) and temporal formulas (2), defined recursively as:

$$\psi ::= \top \mid \mu \mid \neg\mu \mid \psi_1 \wedge \psi_2, \tag{1}$$

$$\phi ::= G_{[a,b]}\psi \mid F_{[a,b]}\psi \mid F_{[\underline{a},\underline{b}]}G_{[\bar{a},\bar{b}]}\psi, \tag{2}$$

where $\neg$, $\wedge$, $G_{[a,b]}$, and $F_{[a,b]}$ denote the negation, conjunction, always and eventually operators, with $a, b \in \mathbb{R}_{\geq 0}$ and $a \leq b$. ψ_1 and ψ_2 in (1) are non-temporal formulas of class (1). To quantify how robustly a trajectory $x : \mathbb{R}_{\geq 0} \to X \subseteq \mathbb{R}^n$ satisfies or violates an STL formula ϕ, we use the concept of robust semantics (Donzé and Maler, 2010, Def. 3), defined as:

$$\begin{aligned}
\rho^{\mu}(x,t) &:= \mathcal{P}(x(t)),\\
\rho^{\neg\phi}(x,t) &:= -\rho^{\phi}(x,t),\\
\rho^{\phi_1\wedge\phi_2}(x,t) &:= \min(\rho^{\phi_1}(x,t), \rho^{\phi_2}(x,t)),\\
\rho^{F_{[a,b]}\phi}(x,t) &:= \max_{t_1\in[t+a,t+b]} \rho^{\phi}(x,t_1),\\
\rho^{G_{[a,b]}\phi}(x,t) &:= \min_{t_1\in[t+a,t+b]} \rho^{\phi}(x,t_1),\\
\rho^{F_{[\underline{a},\underline{b}]}G_{[\bar{a},\bar{b}]}\phi}(x,t) &:= \max_{t_1\in[t+\underline{a},t+\underline{b}]} \min_{t_2\in[t_1+\bar{a},t_1+\bar{b}]} \rho^{\phi}(x,t_2),
\end{aligned}$$

where $\rho^{\phi}(x,t) : X \times \mathbb{R}_{\geq 0} \to \mathbb{R}$ is the *robustness function* of ϕ, such that $\rho^{\phi}(x,t) > 0$ implies that ϕ is satisfied at time t. In order to develop a continuous-time feedback controller that requires the derivative of the robustness function (cf. Theorem 23), $\rho^{\phi_1\wedge\phi_2}(x,t)$ is approximated by the smooth function $\bar{\rho}^{\phi_1\wedge\phi_2}(x,t) = -\frac{1}{\eta}\ln(\exp(-\eta\rho^{\phi_1}(x,t)) + \exp(-\eta\rho^{\phi_2}(x,t)))$ as in Aksaray et al. (2016). Note that, since $\bar{\rho}^{\phi_1\wedge\phi_2}(x,t) \leq \rho^{\phi_1\wedge\phi_2}(x,t)$ for all $\eta > 0$, with equality when $\eta \to \infty$, $\bar{\rho}^{\phi_1\wedge\phi_2}(x,t) > 0$ implies $\rho^{\phi_1\wedge\phi_2}(x,t) > 0$.

As stated in Lindemann and Dimarogonas (2021), satisfaction of an STL formula ϕ with robustness $\rho^{\phi}(x,t)$ can be ensured by enforcing the non-temporal robustness $\rho^{\psi}(x)$ to satisfy

$$-\gamma(t) + \rho^{\max} < \rho^{\psi}(x) < \rho^{\max}, \tag{3}$$

where $\rho^{\max} \in \mathbb{R}_{\geq 0}$, $\gamma(t) = (\gamma^0 - \gamma^\infty)\exp(-lt) + \gamma^\infty$ with $t \in \mathbb{R}_{\geq 0}$, and $l \in \mathbb{R}_{\geq 0}$, γ^0 and $\gamma^\infty \in \mathbb{R}_{>0}$ are chosen such that $\rho^{\phi}(x,t) > 0$ is guaranteed by imposing (3).

2.2 Multi-agent systems

Consider a heterogeneous MAS of N agents $\mathcal{V} = \{1, \ldots, N\}$, where the dynamics of each agent $i \in \mathcal{V}$ is given by:

$$\dot{x}_i(t) = f_i(x_i(t)) + g_i(x_i(t))u_i(t) + w_i(\boldsymbol{x}, t), \tag{4}$$

where $x_i \in \mathbb{R}^{n_i}$ and $u_i \in \mathbb{R}^{m_i}$ denote the state and input of agent i, $f_i : \mathbb{R}^{n_i} \to \mathbb{R}^{n_i}$ is the flow drift, $g_i : \mathbb{R}^{n_i} \to \mathbb{R}^{n_i\times m_i}$ is the input matrix, and $w_i : \bigtimes_{i=1}^{N} \mathbb{R}^{n_i} \times \mathbb{R}_{\geq 0} \to \mathbb{R}^{n_i}$ represents external disturbances acting on i. The global state and input vectors of the MAS are defined as $\boldsymbol{x} := \left[x_1^\top, \ldots, x_N^\top\right]^\top \in \mathbb{R}^n$ and $\boldsymbol{u} := \left[u_1^\top, \ldots, u_N^\top\right]^\top \in \mathbb{R}^m$, where $n = \sum_{i=1}^{N} n_i$ and $m = \sum_{i=1}^{N} m_i$.

Assumption 1. (i) $f_i : \mathbb{R}^{n_i} \to \mathbb{R}^{n_i}$ and $g_i : \mathbb{R}^{n_i} \to \mathbb{R}^{n_i\times m_i}$ are locally Lipschitz continuous, and f_i is unknown; (ii) $g_i(x_i)g_i(x_i)^\top$ is positive definite for all $x_i \in \mathbb{R}^n_i$; (iii) w_i is continuous and uniformly bounded.

Communication graph: the information-exchange structure among the agents is modeled by an undirected graph $\mathcal{G}_C = (\mathcal{V}, \mathcal{E}_C)$, where $\mathcal{V}$ denotes the set of agents and $\mathcal{E}_C \subseteq \mathcal{V}\times\mathcal{V}$ represents the set of communication links. A path between two agents $i, j \in \mathcal{V}$ is defined as a sequence of non-repeating edges that allows j to be reached from i. A k-hop path between i and j corresponds to a path of length k, i.e., a sequence of exactly k edges connecting agent i to j. Given $i, j \in \mathcal{V}$, we denote by D_{ij} the length of the shortest path in $\mathcal{G}_C$ between i and j. For each agent $i \in \mathcal{V}$, $\mathcal{N}_i^{k\text{-hop}} := \{j \in \mathcal{V} \mid \exists\, p\text{-hop path from } j \text{ to } i \text{ with } 2 \leq p \leq k\}$ defines the set of k-hop neighbors of i. The elements of this set are labeled as $\{N_1^i, \ldots, N_{\eta_i}^i\}$, where each $N_j^i \in \mathcal{V}$ denotes the global index of the j-th k-hop neighbor of i, and $\eta_i = |\mathcal{N}_i^{k\text{-hop}}|$ indicates the total number of such neighbors. The set of direct (1-hop) neighbors of agent i in the communication graph is defined as $\mathcal{N}_i^C := \{j \in \mathcal{V} \mid (i,j) \in \mathcal{E}_C \vee j = i\}$.

Task dependency graph: the MAS in (4) is subject to a global STL specification $\phi = \wedge_{i=1}^{N}\phi_i$, where each ϕ_i denotes the local STL specification assigned to agent $i \in \mathcal{V}$. To capture the dependency of task ϕ_i from agents $j \in \mathcal{V}\setminus\{i\}$, a *task dependency graph* $\mathcal{G}_T = (\mathcal{V}, \mathcal{E}_T)$ is introduced, where an edge $(i,j) \in \mathcal{E}_T$ if and only if ϕ_i depends on x_j. We denote by $\mathcal{N}_i^T := \{j \in \mathcal{V} \mid (i,j) \in \mathcal{E}_T \vee j = i\}$ the set of out-neighbors of agent i in the task graph $\mathcal{G}_T$.

Assumption 2. $\mathcal{G}_C$ is a time-invariant, connected and undirected graph, and each $i \in \mathcal{V}$ knows $\mathcal{N}_i^C$ and $\mathcal{N}_i^{k\text{-hop}}$.

Assumption 3. $\mathcal{G}_T$ is a directed acyclic graph. In this context, self-loops do not constitute a cycle and thus are allowed in $\mathcal{G}_T$.

Assumption 2 is not restrictive, since distributed neighborhood discovery algorithms have been extensively studied in the sensor network literature (Chen et al., 2002). Assumption 3 is not limiting, as task assignment can be defined at design stage.

2.3 Cluster-induced graph

Before introducing the concept of clusters, let's define the intersection among graphs as follows.

Definition 4. Given M graphs $\mathcal{G}_i = (\mathcal{V}_i, \mathcal{E}_i)$, $i \in \{1, \dots, M\}$, the intersection graph is defined as $\mathcal{G}^\cap := (\mathcal{V}^\cap, \mathcal{E}^\cap)$, where $\mathcal{V}^\cap := \bigcap_{i=1}^M \mathcal{V}_i$ and $\mathcal{E}^\cap := \bigcap_{i=1}^M \mathcal{E}_i$. For the intersection among directed and undirected graphs, each edge (j, l) of the undirected graph must be considered as existing in both directions, i.e., both as (j, l) and (l, j).

The intersection between the task and communication graphs, i.e., the graph $\mathcal{G}_T \cap \mathcal{G}_C$ defined according to Definition 4, partitions the MAS into N' connected components $\mathcal{C}_l$, referred to as **clusters**. Formally, for $l \in \mathcal{L} := \{1, \dots, N'\}$, $\mathcal{C}_l := (\mathcal{V}_l, \mathcal{E}_l)$, where $\mathcal{V}_l := \{l_1, \dots, l_{v_l}\} \subseteq \mathcal{V}$ denotes the set of v_l agents in the l-th cluster, and $\mathcal{E}_l \subseteq \mathcal{E}_C \cap \mathcal{E}_T$ denotes the set of edges among them. From the definition of *connected components*, $\cup_{l=1}^{N'} \mathcal{V}_l = \mathcal{V}$ and $\mathcal{V}_i \cap \mathcal{V}_j = \emptyset$ hold for all $i, j \in \mathcal{L}$ with $i \neq j$. As a result, each $\mathcal{C}_l$ is associated with $\phi_l^c = \wedge_{l_i \in \mathcal{V}_l} \phi_{l_i}$, and the global STL task ϕ can be rewritten as $\phi = \wedge_{l=1}^{N'} \phi_l^c$.

The cluster-induced graph is then defined as follows.

Definition 5. Given a MAS (4), with communication graph $\mathcal{G}_C$ and task graph $\mathcal{G}_T$, the *cluster-induced graph* is defined as $\mathcal{G}' := (\mathcal{C}', \mathcal{E}')$, where each node in $\mathcal{C}'$ is associated to a cluster $\mathcal{C}_l$, with $l \in \mathcal{L}$, and an edge $(\mathcal{C}_l, \mathcal{C}_j) \in \mathcal{E}'$ exists if and only if there exists a task ϕ_{l_i}, with $l_i \in \mathcal{V}_l$, whose satisfaction depends on the state of an agent $j_q \in \mathcal{V}_j$, with $(l_i, j_q) \in \mathcal{E}_T$.

Remark 6. Note that under Assumption 3, $\mathcal{G}'$ is a directed acyclic graph. Indeed, since $\mathcal{G}'$ is obtained by grouping the agents according to the clusters $\mathcal{C}_l$, no new directed cycles can be introduced.

Assumption 7. Task neighbors within the same cluster are assumed to be in communication. Formally, $\mathcal{N}_{l_i}^T \cap \mathcal{V}_l \subseteq \mathcal{N}_{l_i}^C \cap \mathcal{V}_l$ for all $l_i \in \mathcal{V}_l$, with $l \in \mathcal{L}$.

Assumption 7 ensures that all intra-cluster task dependencies correspond to communication links, allowing the observer and control designs to be decoupled. Since $\mathcal{N}_{l_i}^T \cap \mathcal{V}_l \subseteq \mathcal{N}_{l_i}^T$ and $\mathcal{N}_{l_i}^C \cap \mathcal{V}_l \subseteq \mathcal{N}_{l_i}^C$, Assumption 7 does not enforce $\mathcal{N}_{l_i}^T \setminus \mathcal{N}_{l_i}^C = \emptyset$, nor $\mathcal{N}_{l_i}^C \setminus \mathcal{N}_{l_i}^T = \emptyset$. Consequently, agent $l_i \in \mathcal{V}_l$ may still have tasks involving agents $j_q \in \mathcal{V}_j$, $j \in \mathcal{L} \setminus \{l\}$, with $j_q \in \mathcal{N}_{l_i}^T$ and $j_q \notin \mathcal{N}_{l_i}^C$.

2.4 Individual/collaborative tasks

Consider the local task ϕ_i assigned to agent $i \in \mathcal{V}$. As introduced in Section 2.1, its satisfaction is evaluated through the robustness function $\rho^{\phi_i}(\boldsymbol{x}_{\phi_i}, t)$, where $\boldsymbol{x}_{\phi_i}$ collects the state of agents involved in ϕ_i, i.e., x_j with $j \in \mathcal{N}_i^T$. Satisfaction of ϕ_i may depend on agent i and possibly other agents in $\mathcal{V} \setminus \{i\}$. We say that ϕ_i is **individual** if $\mathcal{N}_i^T = \{i\}$, and **collaborative** otherwise. Collaborative tasks ϕ_i may involve both agents that communicate with i and agents that do not, i.e., $j \in \mathcal{N}_i^T \cap \mathcal{N}_i^C$ and $j \in \mathcal{N}_i^T \setminus \mathcal{N}_i^C$. Thus, since $\boldsymbol{x}_{\phi_i}$ may be partially unavailable to i, we define its local estimate as $\hat{\boldsymbol{x}}_{\phi_i}$, and the corresponding robustness estimate as $\rho^{\phi_i}(\hat{\boldsymbol{x}}_{\phi_i}, t)$. Let $\bar{\boldsymbol{x}}_{\phi_i}$ denote the components of $\hat{\boldsymbol{x}}_{\phi_i}$ corresponding to known states, i.e., x_j with $j \in \mathcal{N}_i^C \cap \mathcal{N}_i^T$, and let $\hat{\boldsymbol{x}}_{\phi_i}^i$ denote those corresponding to estimated states, i.e, x_j with $j \in \mathcal{N}_i^T \setminus \mathcal{N}_i^C$.

Remark 8. $\rho^{\phi_i}(\boldsymbol{x}_{\phi_i}, t) = \rho^{\phi_i}(\hat{\boldsymbol{x}}_{\phi_i}, t)$ under full state knowledge.

Let $N_i^T := \sum_{j \in \mathcal{N}_i^T} n_j$, $N_i^{TC} := \sum_{j \in \mathcal{N}_i^C \cap \mathcal{N}_i^T} n_j$, and $N_i^{T \setminus C} := \sum_{j \in \mathcal{N}_i^T \setminus \mathcal{N}_i^C} n_j$. Then, $\boldsymbol{x}_{\phi_i}, \hat{\boldsymbol{x}}_{\phi_i} \in \mathbb{R}^{N_i^T}$, $\bar{\boldsymbol{x}}_{\phi_i} \in \mathbb{R}^{N_i^{TC}}$, and $\hat{\boldsymbol{x}}_{\phi_i}^i \in \mathbb{R}^{N_i^{T \setminus C}}$. In the sequel, let us denote by $\boldsymbol{x}_{\phi_l^c} := [x_{l_1}^\top, \dots x_{l_{v_l}}^\top]^\top$ the stacked vector of the state of agents in cluster $\mathcal{C}_l$, and by $\hat{\boldsymbol{x}}_{\phi_l^c} := \left[\hat{\boldsymbol{x}}_{\phi_{l_1}}^{l_1\,\top}, \dots, \hat{\boldsymbol{x}}_{\phi_{l_{v_l}}}^{l_{v_l}\,\top}\right]^\top$ the one of the state estimates performed by agent $l_i \in \mathcal{V}_l$ regarding agents $j \in \mathcal{N}_{l_i}^T \setminus \mathcal{N}_{l_i}^C$, i.e., of the agents involved in ϕ_{l_i} but not in communication with l_i itself.

To simplify the notation, we assume without loss of generality that $n_i = 1$ for all $i \in \mathcal{V}$ in the following sections. Nonetheless, the results can be extended to higher dimensions by appropriate use of the Kronecker product.

2.5 State observer

To enable each agent $i \in \mathcal{V}$ to estimate the state of agents $j \in \mathcal{N}_i^T \setminus \mathcal{N}_i^C$, we employ the decentralized k-hop Prescribed Performance State Observer (k-hop PPSO) proposed in Zaccherini et al. (2025c), with

$$k = \max_{i \in \mathcal{V}, j \in (\mathcal{N}_i^T \setminus \mathcal{N}_i^C)} D_{ij}, \tag{5}$$

where D_{ij} is defined as in Section 2.2. For clarity, the observer structure is recalled in this subsection.

Denote by $\boldsymbol{x}^i := [x_{N_1^i}^\top, \dots, x_{N_{\eta_i}^i}^\top]^\top$ the vector of states $x_{N_j^i}$ of the k-hop neighbors of agent i, and let $\hat{\boldsymbol{x}}^i := [\hat{x}_{N_1^i}^{i\,\top}, \dots, \hat{x}_{N_{\eta_i}^i}^{i\,\top}]^\top$ be the vector containing their estimate carried out by i. The state estimation error is then defined as $\tilde{\boldsymbol{x}}^i := \hat{\boldsymbol{x}}^i - \boldsymbol{x}^i = [\tilde{x}_{N_1^i}^{i\,\top}, \dots, \tilde{x}_{N_{\eta_i}^i}^{i\,\top}]^\top$, where $\tilde{x}_{N_j^i}^i := \hat{x}_{N_j^i}^i - x_{N_j^i}$ for all $N_j^i \in \mathcal{N}_i^{k\text{-hop}}$. For all $i \in \mathcal{V}$ and $r \in \mathcal{N}_i^{k\text{-hop}}$, let $\delta_r^i(t)$ and $\rho_r^i(t)$ be prescribed performance functions satisfying $\|\boldsymbol{\rho}_r(t)\| \leq \alpha \min_{i \in \mathcal{N}_r^{k\text{-hop}}} \{\delta_r^i(t)\}$, where $\boldsymbol{\rho}_r(t) := \left[\rho_r^{N_1^r}(t), \dots, \rho_r^{N_{\eta_r}^r}(t)\right]^\top$, and $\alpha \in \mathbb{R}_{>0}$ is a constant parameter related to the communication graph topology (Zaccherini et al., 2025c). Formally, the prescribed performance functions $\delta_r^i(t)$ and $\rho_r^i(t)$ are defined as follows.

Definition 9. (Zaccherini et al. (2025c)). A function $\rho : \mathbb{R}_{\geq 0} \to \mathbb{R}$ is a prescribed performance function if it satisfies, for all $t \in \mathbb{R}_{\geq 0}$: (i) $\rho \in \mathcal{C}^1$; (ii) $0 < \rho(t) \leq \overline{\rho}$ for some $\overline{\rho} < \infty$ and (iii) $|\dot{\rho}(t)| \leq \overline{\rho}_d$ for some $\overline{\rho}_d < \infty$.

For all $i \in \mathcal{V}$ and $r \in \mathcal{N}_i^{k\text{-hop}}$, let $\hat{x}_r^i$ evolve according to

$$\dot{\hat{x}}_r^i = -\rho_r^i(t)^{-1} J(e_r^i) \epsilon_r^i(t), \tag{6}$$

where $J(e_r^i) := \ln(\frac{2}{1-(e_r^i)^2})$, $e_r^i := \rho_r^i(t)^{-1} \xi_r^i$ with $\xi_r^i := \sum_{l \in (\mathcal{N}_i^C \cap \mathcal{N}_r^{k\text{-hop}})} (\hat{x}_r^i - \hat{x}_r^l) + |\mathcal{N}_i^C \cap \mathcal{N}_r^C| (\hat{x}_r^i - x_r)$, and $\epsilon_r^i(t) := \ln(\frac{1+e_r^i}{1-e_r^i})$. Then, according to (Zaccherini et al., 2025c, Thm. 2, Rem. 7), the observer in (6) guarantees $|\tilde{x}_r^i(t)| < \delta_r^i(t)$ for all $i \in \mathcal{V}$, $r \in \mathcal{N}_i^{k\text{-hop}}$ and $t \in \mathbb{R}_{\geq 0}$.

Remark 10. As reported in (Zaccherini et al., 2025c, Thm. 2, Rem. 7), the result above holds as long as $g_i(x_r) u_i$ is bounded and the dynamics (4) remain within bounded sets $\mathcal{X}_i \subset \mathbb{R}^{n_i}$. As shown in the proof of Theorem 23, this condition is not restrictive in the proposed framework.

Once every $i \in \mathcal{V}$ can estimate the state of agents $j \in \mathcal{N}_i^T \setminus \mathcal{N}_i^C$, the control problem can be formulated as follows.

Problem 11. Consider a heterogeneous MAS (4) with connected communication graph $\mathcal{G}_C$ and global STL specification $\phi = \wedge_{i=1}^{N}\phi_i$, where ϕ_i denotes the local STL task of agent i. For each $i \in \mathcal{V}$, synthesize a decentralized controller u_i that guarantees satisfaction of ϕ using only locally available information.

3. OBSERVER-BASED TASK SATISFACTION

As introduced in Section 2.1, to ensure satisfaction of the STL formula ϕ_i, the non-temporal robustness $\rho^{\psi_i}(\boldsymbol{x}_{\phi_i})$ must satisfy:

$$-\gamma_{\psi_i}(t) + \rho_{\psi_i}^{\max} < \rho^{\psi_i}(\boldsymbol{x}_{\phi_i}) < \rho_{\psi_i}^{\max}, \tag{7}$$

where $\boldsymbol{x}_{\phi_i}$ collects the states involved in task ϕ_i, and $\gamma_{\psi_i}(t)$ is a positive, decreasing exponential function as in (3), where $\gamma_{\psi_i}^0, \gamma_{\psi_i}^\infty, l_{\phi_i}, t_{\phi_i}^*, r_{\phi_i}$, and $\rho_{\psi_i}^{\max}$ are defined and tuned as in Liu et al. (2025)[Remark 23].

Remark 12. $\gamma_{\psi_i}(t)$ in (3) is a valid prescribed performance function according to Definition 9.

Since the robustness ρ^{ψ_i} may depend on estimated rather than actual states, inequality (7) cannot be enforced directly. However, since the k-hop PPSO introduced in Section 2.5 guarantees prescribed performances on the state estimation errors regardless of the system trajectory, we can formulate an analogous constraint on $\rho^{\psi_i}(\hat{\boldsymbol{x}}_{\phi_i})$ that ensures task satisfaction under the worst-case estimation error. To this end, we introduce the following assumption.

Assumption 13. For all $i \in \mathcal{V}$, there exists a prescribed performance function $\rho_{\psi_i}^t : \mathbb{R}_{\geq 0} \to \mathbb{R}$, defined as in Definition 9, such that

$$0 < \rho^{\psi_i}(\hat{\boldsymbol{x}}_{\phi_i}(t)) - \rho_{\psi_i}^t(t) \implies 0 < \rho^{\psi_i}(\boldsymbol{x}_{\phi_i}(t)). \tag{8}$$

Assumption 13 is not restrictive in practice. Indeed, since: (i) $\boldsymbol{x}^i = \hat{\boldsymbol{x}}^i - \tilde{\boldsymbol{x}}^i$ holds by definition; (ii) $\|\tilde{\boldsymbol{x}}^i\| < \|[\delta^i_{N_1^i}(t), \ldots, \delta^i_{N_{\eta_i}^i}(t)]\|$ is guaranteed for all $i \in \mathcal{V}$ by the k-hop PPSO in (6); and (iii) $\|[\delta^i_{N_1^i}(t), \ldots, \delta^i_{N_{\eta_i}^i}(t)]\|$ is a prescribed performance function (Zaccherini et al., 2025c, Lemma 2); Assumption 13 holds for common STL tasks. For clarity, an example of a formation/containment task is presented below.

Example 14. Consider a path graph with $N = 4$ agents and denote the global state as $\boldsymbol{x} = [x_1\ x_2\ x_3\ x_4]^\top \in \mathbb{R}^n$, where $n = 4$. Assume $\mathcal{N}_1^{\text{3-hop}} = \{3, 4\}$ and $\mathcal{N}_1 = \{2\}$. Suppose agent 1 is assigned a task ϕ_1 with non-temporal robustness function $\rho^{\psi_1}([x_1, x_3]^\top) := r_{13}^2 - |x_1 - x_3 - d_{13}|^2$, where $r_{13}, d_{13} \in \mathbb{R}_{\geq 0}$. Since $x_3 = \hat{x}_3^1 - \tilde{x}_3^1$ from definition,

$$r_{13}^2 - |x_1 - \hat{x}_3^1 + \tilde{x}_3^1 - d_{13}|^2 > 0 \tag{9}$$

holds for all $t \in \mathbb{R}_{\geq 0}$. Then, since $|x_1 - \hat{x}_3^1 - d_{13} + \tilde{x}_3^1|^2 \leq (|x_1 - \hat{x}_3^1 - d_{13}| + |\tilde{x}_3^1|)^2$ is valid from triangle inequality, (9) is satisfied if $r_{13}^2 - (|x_1 - \hat{x}_3^1 - d_{13}| + |\tilde{x}_3^1|)^2 > 0$. Since $r_{13}^2 - |x_1 - \hat{x}_3^1 - d_{13}|^2 - |\tilde{x}_3^1|^2 - 2|x_1 - \hat{x}_3^1 - d_{13}||\tilde{x}_3^1| > 0$ holds in $|x_1 - \hat{x}_3^1 - d_{13}| \in (0, -|\tilde{x}_3^1| + r_{13})$, by introducing the bound resulting from the k-hop PPSO, i.e., $0 < |\tilde{x}_3^1| < \delta_3^1(t)$, we derive that the previous inequality is satisfied if $|x_1 - \hat{x}_3^1 - d_{13}| < -\delta_3^1(t) + r_{13}$, with $\delta_3^1(t) < r_{13}$. By squaring both sides, we notice that $0 < \rho^{\psi_1}([x_1, \hat{x}_3^1]^\top) - \rho_{\psi_i}^t$ implies (9) with $\rho^{\psi_1}([x_1, \hat{x}_3^1]^\top) = r_{13}^2 - |x_1 - \hat{x}_3^1 - d_{13}|^2$ and $\rho_{\psi_i}^t(t) = 2\delta_3^1(t) r_{13} - \delta_3^1(t)^2$. Thus, Assumption 13 holds.

Given Assumption 13, guaranteeing the satisfaction of ϕ_i in presence of state estimates reduces to enforcing $-\gamma_{\psi_i}(t) + \rho_{\psi_i}^{\max} < \rho^{\psi_i}(\hat{\boldsymbol{x}}_{\phi_i}) - \rho_{\psi_i}^t(t) < \rho_{\psi_i}^{\max} - \rho_{\psi_i}^t(t)$, where $\gamma_{\psi_i}(t)$ is defined as in (7) and $\rho^{\psi_i}(\hat{\boldsymbol{x}}_{\phi_i})$ as in Section 2.4. Equivalently, the following condition must be enforced with $\Gamma_{\psi_i}(t) = \gamma_{\psi_i}(t) - \rho_{\psi_i}^t(t)$:

$$-\Gamma_{\psi_i}(t) < \rho^{\psi_i}(\hat{\boldsymbol{x}}_{\phi_i}) - \rho_{\psi_i}^{\max} < 0. \tag{10}$$

Note that (10) resembles the structure in (7). Thus, to guarantee the possibility of applying a PPC inspired controller, the following assumption is introduced on $\Gamma_{\psi_i}(t)$.

Assumption 15. $\Gamma_{\psi_i}(t) > 0$ for all $t \in \mathbb{R}_{\geq 0}$.

Since $\gamma_{\psi_i}(t)$ and $\rho_{\psi_i}^t(t)$ are affected by design choices, Assumption 15 is not restrictive in practice.

Given Assumption 15, the following holds for $\Gamma_{\psi_i}(t)$.

Lemma 16. $\Gamma_{\psi_i}(t)$ is a prescribed performance function as per Definition 9.

Proof. For space limitations, the proof is omitted; see Zaccherini et al. (2025b) for details.

Remark 17. For collaborative tasks ϕ_i for which $\mathcal{N}_i^T \setminus \mathcal{N}_i^C = \emptyset$, i.e., tasks involving only communicating agents, $\hat{\boldsymbol{x}}_{\phi_i} \equiv \boldsymbol{x}_{\phi_i}$ holds. Consequently, $\rho_{\psi_i}^t(t) = 0$ for all t and condition (10) reduces to (7).

To handle tasks ϕ_i of the form (2), where the non-temporal formula ψ_i is obtained as the conjunction of p_i formulas, i.e., $\psi_i = \wedge_{j=1}^{p_i}\psi_{i,j}$, we exploit the following properties of the always (G) and eventually (F) temporal operators:

$$\begin{aligned} &G_{[a,b]}\psi_i = \wedge_{j=1}^{p_i} G_{[a,b]}\psi_{i,j}, \\ &F_{[a,b]}\psi_i = G_{[\tau,\tau]}\psi_i \text{ with } \tau \in [a, b]. \end{aligned} \tag{11}$$

Given the validity of (11), each $\gamma_{\psi_{i,j}}(t)$ can be designed and tuned individually to obtain $\Gamma_{\psi_{i,j}}(t)$ for all $j \in \{1, \ldots, p_i\}$. The satisfaction of ψ_i is then enforced by constraining $-\Gamma_{\psi_i}(t) < \rho^{\psi_i}(\hat{\boldsymbol{x}}_{\phi_i}) - \rho_{\psi_i}^{\max} < 0$ as in (10), with $\Gamma_{\psi_i}(t) = \min_{j \in \{1,\ldots,p_i\}} \Gamma_{\psi_{i,j}}(t) \geq -\frac{1}{\eta}\ln(\sum_{j=1}^{p_i}\exp(-\eta\Gamma_{\psi_{i,j}}(t))$ and robustness $\rho^{\psi_i}(\hat{\boldsymbol{x}}_{\phi_i}) = \min_{j\in\{1,\ldots,p_i\}} \rho^{\psi_{i,j}}(\hat{\boldsymbol{x}}_{\phi_i}) \geq -\frac{1}{\eta}\ln(\sum_{j=1}^{p_i}\exp(-\eta\rho^{\psi_{i,j}}(\hat{\boldsymbol{x}}_{\phi_i}))$.

Based on (10), Problem 11 can be reformulated as:

Problem 18. Consider a heterogeneous MAS (4) with a cluster-induced graph $\mathcal{G}'$ as in Definition 5, where each agent employs the k-hop PPSO (6). Design a control law u_i that guarantees (10) for all $i \in \mathcal{V}$ and all $t \in \mathbb{R}_{\geq 0}$.

4. DECENTRALIZED OBSERVER-BASED CONTROLLER

Inspired by Lindemann and Dimarogonas (2021); Liu et al. (2025), this section leverages the concept of Prescribed Performance Control (PPC) (Bechlioulis and Rovithakis, 2008) to address Problem 18.

Under Assumption 15, let $e^{\psi_i}(\hat{\boldsymbol{x}}_{\phi_i}, t) := \Gamma_{\psi_i}^{-1}(t)(\rho^{\psi_i}(\hat{\boldsymbol{x}}_{\phi_i}) - \rho_{\psi_i}^{\max})$ be the normalized error. The transformed error $\epsilon^{\psi_i}(\hat{\boldsymbol{x}}_{\phi_i}, t)$ is then defined as

$$\epsilon^{\psi_i}(\hat{\boldsymbol{x}}_{\phi_i}, t) := T_{\psi_i}(e^{\psi_i}(\hat{\boldsymbol{x}}_{\phi_i}, t)), \tag{12}$$

where $T_{\psi_i} : (-1, 0) \to \mathbb{R}$ is a strictly increasing transformation given by $T_{\psi_i}(e^{\psi_i}(\hat{\boldsymbol{x}}_{\phi_i}, t)) := \ln\left(-\frac{e^{\psi_i}(\hat{\boldsymbol{x}}_{\phi_i}, t)+1}{e^{\psi_i}(\hat{\boldsymbol{x}}_{\phi_i}, t)}\right)$.

Furthermore, denote by $J_{\psi_i}(e^{\psi_i}) := \frac{\partial T_{\psi_i}}{\partial e^{\psi_i}} = -\frac{1}{e^{\psi_i}(e^{\psi_i}+1)}$ the Jacobian of T_{ψ_i}. The main idea of PPC is to design control policies u_i that keep $\epsilon^{\psi_i}(\hat{\boldsymbol{x}}_{\phi_i}, t)$ bounded, thereby ensuring satisfaction of (10). To this end, consider the following assumption on ρ^{ψ_i}.

Assumption 19. Each formula ψ_i is such that: (i) $\rho^{\psi_i} : \mathbb{R}^{N_i^T} \to \mathbb{R}$ is concave with $\frac{\partial \rho^{\psi_i}(\boldsymbol{x}_{\phi_i})}{\partial x_i} = 0_n$ only at the global maximum (ii) ρ^{ψ_i} is continuously differentiable with respect to $\boldsymbol{x}_{\phi_i}$ or smooth almost everywhere except from the global maximum and (iii) the formula is well-posed in the sense that for all $C \in \mathbb{R}$ there exists $0 \leq \bar{C} < \infty$ such that for all $\boldsymbol{x}_{\phi_i}$ with $\rho^{\psi_i}(\boldsymbol{x}_{\phi_i}) \geq C$, $\|\boldsymbol{x}_{\phi_i}\| \leq \bar{C}$ holds.

Remark 20. Since linear functions and those modeling containment or formation tasks are concave, condition (i) of Assumption 19 is not restrictive. Moreover, each ϕ_i can be augmented with $\psi_i^{\text{Bound}} := (\|\boldsymbol{x}_{\phi_i}\| < \bar{C}_i)$, where choosing $\bar{C}_i$ sufficiently large to preserve feasibility ensures that condition (iii) of Assumption 19 is satisfied under proper task assignment and a convergent observer. For collaborative tasks, only $\bar{\boldsymbol{x}}_{\phi_i}$ can be directly bounded by ψ_i^{Bound}. Nevertheless, under Assumption 3 and a convergent observer, it suffices to add $\psi_j^{\text{Bound}} := (\|\bar{\boldsymbol{x}}_{\phi_j}\| < \bar{C}_j)$ to each ψ_j that do not satisfy (iii) in order to guarantee boundedness of $\|\hat{\boldsymbol{x}}_{\phi_i}\|$, and thus ensure that condition (iii) holds.

Define the global optimum as $\rho_{\psi_i}^{\text{opt}} := \sup_{\boldsymbol{x}_{\phi_i}} \rho^{\psi_i}(\boldsymbol{x}_{\phi_i})$. Given the concavity of ρ^{ψ_i} from Assumption 19, to avoid $\frac{\partial \rho^{\psi_i}(\boldsymbol{x}_{\phi_i})}{\partial x_i} = 0_n$ along the transient, and thus feasibility issue, it suffices to tune $\rho_{\psi_i}^{\max}$ so that $0 < \rho_{\psi_i}^{\max} < \rho_{\psi_i}^{\text{opt}}$.

For given observer prescribed performances $\delta_{N_j^i}^i(t)$, with $N_j^i \in \mathcal{N}_i^{k\text{-hop}}$, ensuring the satisfiability of ϕ_i regardless of $\hat{\boldsymbol{x}}_{\phi_i}$, for every $i \in \mathcal{V}$, requires the following.

Assumption 21. (i) $\rho_{\psi_i}^{\max} - \max_{\tau \in T_{\phi_i}^{\text{wdw}}} \rho_{\psi_i}^t(\tau) > 0$ for all $i \in \mathcal{V}$, where $T_{\phi_i}^{\text{wdw}}$ represents the time window over which ϕ_i must be satisfied; (ii) $\hat{\rho}_{\psi}^{\text{opt}} := \sup_{\boldsymbol{x}}\{\min_{i\in\mathcal{V}}[\rho^{\psi_i}(\boldsymbol{x}_{\phi_i}) - \max_{\tau \in T_{\phi_i}^{\text{wdw}}} \rho_{\psi_i}^t(\tau)]\}$ satisfies $\hat{\rho}_{\psi}^{\text{opt}} > 0$.

Assumption 21 represents a feasibility condition for given $\delta_{N_j^i}^i(t)$ and $\rho_{\psi_i}^{\max}$. However, since $\rho_{\psi_i}^t(t)$ depends on $\delta_{N_j^i}^i(t)$, which is a design choice, Assumption 21 can be satisfied whenever $\rho_{\psi}^{\text{opt}} := \sup_{\boldsymbol{x}}\{\min_{i\in\mathcal{V}} \rho^{\psi_i}(\boldsymbol{x}_{\phi_i})\} > 0$ by appropriate design of $\delta_{N_j^i}^i(t)$ and $\rho_{\psi_i}^{\max}$. Thus, the assumption is not restrictive. For always operators $G_{[a,b]}\phi_i$, $T_{\phi_i}^{\text{wdw}} = [a, b]$, while for eventually operators $F_{[a,b]}\phi_i$, $T_{\phi_i}^{\text{wdw}} = \{t^*\}$, where $t^* \in [a, b]$ is the time instant of task satisfaction, as per Section 3 and Lindemann and Dimarogonas (2021). To present our main result, an additional assumption is required.

Assumption 22. $-\Gamma_{\psi_i}(0) < \rho^{\psi_i}(\hat{\boldsymbol{x}}_{\phi_i}(0)) - \rho_{\psi_i}^{\max} < 0$ and $|\xi_{N_j^i}^i(0)| < \rho_{N_j^i}^i(0)$ hold for all $i \in \mathcal{V}$ and $N_j^i \in \mathcal{N}_i^{k\text{-hop}}$.

Assumption 22 involves only design parameters and initialization quantities. Therefore, it's not restrictive. With

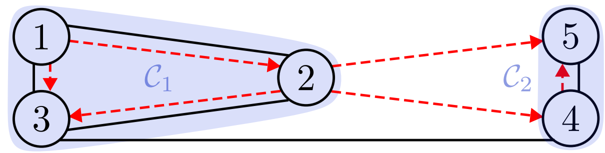


Fig. 1. Graphs $\mathcal{G}_C$ and $\mathcal{G}_T$, respectively in solid and dashed lines. The shadow areas represent the induced clusters, i.e., $\mathcal{C}_1$ and $\mathcal{C}_2$.

the defined notation and assumptions, we are now ready to state the main result of this work.

Theorem 23. Consider a MAS (4) with communication graph $\mathcal{G}_C$, and task graph $\mathcal{G}_T$ induced by a global task $\phi = \wedge_{i=1}^N \phi_i$. Suppose each agent runs the k-hop PPSO in (6) with k selected according to (5). Consider the agents belonging to the cluster $\mathcal{C}_l$, subject to the task $\phi_l^c = \wedge_{l_i \in \mathcal{V}_l} \phi_{l_i}$. Then, ϕ_l^c is satisfied, for all $l \in \mathcal{L}$, if Assumptions 2, 3, 7, 13, 15, 19, 21, 22 hold and each agent $l_i \in \mathcal{V}_l$ applies the decentralized controller

$$u_{l_i} = -g_{l_i}^\top(x_{l_i}(t)) \sum_{l_j \in \mathcal{V}_l} \frac{\partial \rho^{\psi_{l_j}}(\hat{\boldsymbol{x}}_{\phi_{l_j}})}{\partial x_{l_i}} \Gamma_{\psi_{l_j}}^{-1} J_{\psi_{l_j}} \epsilon^{\psi_{l_j}}, \qquad (13)$$

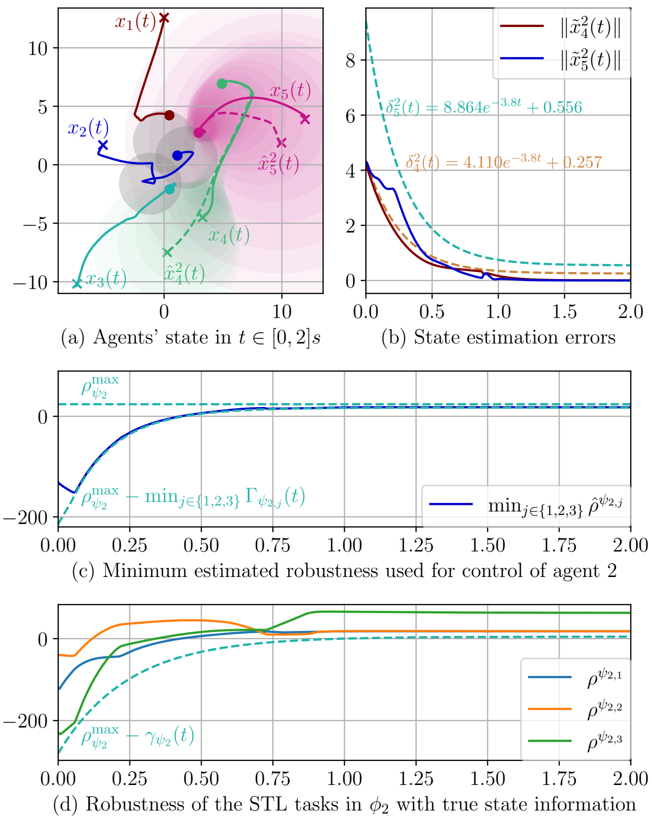
where $\Gamma_{\psi_{l_j}}$ is defined as in (10), and $J_{\psi_{l_j}}$, $\epsilon^{\psi_{l_j}}$ as in (12).

Proof. For space limitations, the proof is omitted; see Zaccherini et al. (2025b) for details.

Remark 24. If g_{l_i} in (4) is a square symmetric matrix with known sign, then $u_{l_i} = -s_{l_i} \sum_{l_j \in \mathcal{V}_l} \frac{\partial \rho^{\psi_{l_j}}(\hat{\boldsymbol{x}}_{\phi_{l_j}})}{\partial x_{l_i}} \Gamma_{\psi_{l_j}}^{-1} J_{\psi_{l_j}} \epsilon^{\psi_{l_j}}$ ensures Problem 11 to be solved with $s_{l_i} = 1$ if g_i is positive definite and $s_{l_i} = -1$ otherwise.

5. SIMULATION

Consider the MAS in Fig. 1, composed of $N = 5$ agents communicating according to the connected graph $\mathcal{G}_C$. Suppose each agent behaves as $\dot{x}_i = f(x_i) + g(x_i)u_i + w_i(t)$, where $x_i = [x_{i,1}, x_{i,2}]^\top$ and $u_i \in \mathbb{R}^2$ are the state and input vectors, $f(x_i) = [x_{i,1} + 2x_{i,2} + 0.6\arctan(x_{i,1}) + 0.3\tanh(0.8x_{i,2}), 3x_{i,1} + 4x_{i,2} + 0.5\sin(0.7x_{i,1} + 0.2x_{i,2}) + 0.4\arctan(0.5x_{i,2})]^\top$, $g(x_i) = \begin{bmatrix} \cos(0.5x_{i,2}) & -\sin(0.5x_{i,2}) \\ \sin(0.5x_{i,2}) & \cos(0.5x_{i,2}) \end{bmatrix}$, and $w_i(t) = [w_{i,1}, w_{i,2}]^\top$ is a random disturbance with $w_{i,1}, w_{i,2} \in [-6, 6]$. Assume the agents are subject to the following STL tasks: $\phi_1 = G_{[1,2]}((\|x_1 - [0,2]^\top\| \leq 7) \wedge (\|x_1 - x_2\|^2 \leq 26.75) \wedge (\|x_1 - x_3\|^2 \leq 70.05))$, $\phi_2 = G_{[1,2]}((\|x_2 - x_3\|^2 \leq 26.75) \wedge (\|x_2 - x_4\|^2 \leq 70.05) \wedge (\|x_2 - x_5\|^2 \leq 70.05))$, $\phi_3 = G_{[1,2]}(\|x_3 - [-1.175, -1.618]^\top\|^2 \leq 7)$, $\phi_4 = G_{[1,2]}(\|x_4 - x_5\|^2 \leq 26.75)$, $\phi_5 = G_{[1,2]}(\|x_5 - [1.9, 0.618]^\top\|^2 \leq 7)$. Intuitively, all agents are required to get sufficiently close to each other, while allowing agents 1, 3 and 5 to reach their goal positions. From the task and communication graph, respectively $\mathcal{G}_T$ and $\mathcal{G}_C$ in Fig. 1, the MAS is split into $N' = 2$ clusters, i.e., $\mathcal{C}_1$ and $\mathcal{C}_2$ with $\mathcal{V}_1 = \{1, 2, 3\}$ and $\mathcal{V}_2 = \{4, 5\}$. Since agents 4 and 5 are not in communication with 2, to allow the satisfaction of ϕ_2 we leverage the observer introduced in Section 2.5 with $k = 3$. To guarantee the satisfaction of the tasks by means of the controller (13), the function γ_2 is adjusted, following Example 14, to account



(a) Agents' state in $t \in [0, 2]s$

(b) State estimation errors

(c) Minimum estimated robustness used for control of agent 2

(d) Robustness of the STL tasks in ϕ_2 with true state information

Fig. 2. (a) State and estimation trajectories; initial states are represented by crosses, terminal state by dots. The pink and green areas represent the evolution of the state uncertainties with time; the gray circles are the target areas of the individual tasks. (b) Evolution of the norm of the state estimation errors performed by agent 2; the dashed lines are the prescribed performance functions of the k-hop PPSO. (c) Minimum estimated robustness of ϕ_2. (d) Robustness of tasks in ϕ_2 with true state information.

for the worst-case estimation errors. Given $\mathcal{G}_C$ and $\mathcal{G}_T$ in Fig. 1, by proper system initialization and observer specifications, Assumptions 2-22 are satisfied. Thus, Theorem 23 holds and (13) guarantees tasks satisfaction.

Fig. 2(a) shows the MAS trajectory, along with the time evolution of the state estimates required for task ϕ_2 and the corresponding uncertainty regions due to estimation errors. Due to space limitations, Figs. 2(b)-(d) present only the results for agent 2. As illustrated in Figs. 2(c)-(d), enforcing $\min_{j\in\{1,2,3\}} \hat{\rho}^{\psi_{2,j}} > 0$ for all $t \in [1, 2]$ by imposing (10), with $\Gamma_{\psi_2}(t) = \min_{j\in\{1,2,3\}} \Gamma_{\psi_{2,j}}$, is sufficient to guarantee satisfaction of ϕ_2. Indeed, Fig. 2(d) shows that $\rho^{\psi_{2,j}} > 0$ for all $j \in \{1, 2, 3\}$ and $t \in [1, 2]$.

6. CONCLUSION AND FUTURE WORK

We proposed a decentralized observer-based controller for MAS subject to STL specifications under communication/task graphs mismatch. Given its structure and decentralized nature, the proposed solution is robust to bounded external disturbances and suitable for large-scale heterogeneous systems. Future works will address the observer-controller co-design to relax Assumption 7.

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