Decentralized Semantic Communication and Cooperative Tracking Control for a UAV Swarm over Wireless MIMO Fading Channels

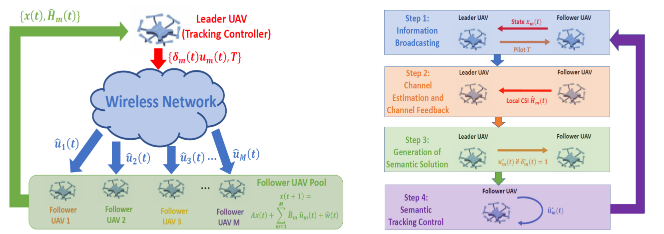
Minjie Tang, *Member, IEEE*, Chenyuan Feng, *Member, IEEE*, and Tony Q. S. Quek, *Fellow, IEEE*

***Abstract*—Conventional communication strategies in UAV swarms often lead to excessive bandwidth consumption and energy overhead due to frequent exchange of control signals. Inspired by the semantic communication paradigm—which emphasizes transmitting only task-relevant information—we propose a cooperative semantic communication-control framework that selectively transmits the most informative control data. This approach significantly reduces communication burden and power consumption while maintaining accurate swarm coordination. Specifically, we consider a UAV swarm composed of one leader and multiple followers, interconnected through unreliable MIMO wireless channels. We first develop a dynamic model that captures both inter-UAV interactions and MIMO channel imperfections. Incorporating power costs, we formulate the joint communication and cooperative tracking control problem as a drift-plus-penalty optimization. A closed-form decentralized solution is then derived, adapting to tracking errors and local channel conditions. Using Lyapunov drift analysis, we establish sufficient conditions for swarm stability. Numerical simulations demonstrate that the proposed scheme substantially outperforms existing methods in both tracking accuracy and communication efficiency.**

***Index Terms*—UAV tracking control, semantic communication, decentralized control, MIMO channels, Lyapunov drift analysis.**

I. Introduction

Cooperative tracking control for UAV swarms has garnered substantial interest across both the industrial and academic realms, owing to its broad applications in fields such as surveillance and agricultural monitoring [1], [2]. A typical UAV swarm, comprising a group of *follower UAVs* and a *leader controller UAV*, is depicted in Fig. 1(a). The leader UAV monitors the real-time states of the follower UAVs—including their position, speed, and angular velocity—and intermittently generates tracking control signals that are transmitted to the follower UAVs via an unreliable wireless network. Upon reception of these control directives, the follower UAVs adjust their states to conform to predetermined target profiles. The wireless network connecting the follower UAVs and the leader UAV is susceptible to a myriad of impairments, such as signal fading and channel noise, which has the potential to markedly degrade the tracking control efficacy of a UAV swarm.



(a) Typical architecture of a UAV swarm. (b) Methodology of the proposed scheme.

Fig. 1: Illustration of the UAV swarm system.

Designing effective tracking controllers for UAV swarms operating over wireless networks presents significant challenges, due to the stochastic, time-varying, and unreliable nature of real-world channels. Most prior studies simplify the problem by assuming static communication conditions. For example, classical control techniques such as pole placement and Proportional-Integral-Derivative (PID) controllers have been widely studied under the stable channel assumption [2]–[6]. While they are intuitive and easy to deploy, they often rely on heuristic parameter tuning and lack theoretical guarantees for stability and performance under dynamic network conditions. To overcome these limitations, linear optimal tracking controllers based on Generalized Algebraic Riccati Equation (GARE) have been developed [7], [8]. These methods optimize control gains through the solution of Linear Quadratic Regulator (LQR) problem, balancing tracking accuracy and control effort. However, such approaches typically assume perfect communication, ignoring the effects of packet loss, fading, or interference. In practical scenarios, UAV swarms must coordinate over dynamic wireless links that exhibit random fading, interference, and potentially time-varying topology. Applying controllers designed for idealized conditions in these settings can lead to suboptimal or even unstable behavior. Several recent efforts have begun to consider unreliable communication, but many rely on oversimplified models. For instance, some works [1], [9] employ finite-state erasure models to simulate packet loss, while others [10], [11] account for occasional communication failures without modeling realistic fading processes. Other approaches [12]–[14] address bounded communication delays through pre-characterized latency bounds, yet they still neglect the stochastic nature of wireless fading. As a result, designing tracking controllers that explicitly incorporate time-varying channel dynamics remains an open issue.

In addition to control accuracy, communication efficiency

Minjie Tang and Chenyuan Feng are with the Department of Communication Systems, EURECOM, France (e-mail: {Minjie.Tang, Chenyuan.Feng}@eurecom.fr).

Tony Q. S. Quek is with the Information Systems Technology and Design Pillar, Singapore University of Technology and Design, Singapore (e-mail: tonyquek@sutd.edu.sg).

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Corresponding Author: Chenyuan Feng.

TABLE I: Comparison with Representative Prior Work.

Ref.	Channel Model	Control Law	Communication Trigger Law	Control or Communication Triggering Law Adapt to Channel	Stability under Random Fading Channels
[3]	Static	Pole Placement	N/A	N/A	No
[4]–[6]	Static	PID	N/A	N/A	No
[7], [8]	Static	LQR (Riccati)	N/A	N/A	No
[9]–[11]	Packet Dropout	Heuristic Linear Law	N/A	Adapt to Channel ON-OFF Realization	No
[12]–[14]	Static delay	Consensus Law	N/A	Adapt to Static Delay Model	No
[15]–[18]	Resource Constrained	Scheduling-based	Rate-Aware	Adapt to Channel Statistics	N/A
[19]–[24]	Static	State-Dependent	State-Triggered	No	No
Ours	**MIMO Random Fading**	**Lyapunov-based**	**Semantic (State+Channel) Triggered**	**Adapt Time-varying Channel Realization**	**Yes**

is also a key consideration in UAV swarm operations. Several studies [15]–[18] optimize UAV trajectories and scheduling under power or delay constraints, but focus primarily on throughput or delay rather than control stability. For example, [15], [16] address mobile relaying, while [17], [18] explore joint trajectory and link optimization. These works, however, do not account for real-time channel impact on control. To improve efficiency in control-communication systems, [19] proposes a periodic policy, but fixed schedules can be wasteful or too slow. The emerging field of semantic communications offers a promising alternative by transmitting only task-relevant or semantically meaningful information [25]–[27]. In the context of swarm control, this motivates selective communication policies that prioritize control updates with the greatest impact on task performance. State-dependent semantic communication strategies [20]–[23] attempt to reduce communication load by triggering transmissions based on tracking error thresholds. However, these methods often overlook real-time wireless channel conditions. Recently, [24] proposed an event-triggered distributed model predictive control framework for multi-UAV systems, demonstrating the benefits of adaptive communication under constrained settings. However, the adopted communication model assumes static channels and fails to capture the statistical dynamics of fading.

Given these limitations, it is essential to explore state- and channel-dependent communication and control strategies that can adapt to realistic time-varying wireless environments. To the best of our knowledge, this is the first work to tackle this challenge by proposing a decentralized semantic communication and cooperative tracking control framework for a UAV swarm over wireless MIMO fading channels. The key distinctions between our approach and representative prior works are summarized in Table I. The main contributions are summarized as follows: **i) Semantic Communication over MIMO Fading Channels:** We introduce an efficient communication strategy that considers both power cost and tracking stability. The resulting policy has a semantic structure, adapting to real-time tracking errors and local channel conditions. **ii) Semantic Tracking Control under Wireless Fading:** To avoid solving complex Bellman equations [28], we develop a low-complexity control algorithm that minimizes Lyapunov drift based on UAV states and local CSI, which is semantically structured and fully decentralized. **iii) Closed-form Stability Guarantee:** Using Lyapunov analysis, we derive a closed-form sufficient condition for tracking stability under proposed semantic communication and control policy.

TABLE II: Main Notations & Definitions

Notation	Definition / Physical Meaning
$\mathbf{x}(t)$	Global system state of the UAV swarm at timeslot t
$\mathbf{x}_m(t)$	System state of UAV m at timeslot t
$\mathbf{r}(t)$	Target UAV state at timeslot t
$\mathbf{u}_m(t)$	Remote tracking control signal for UAV m at timeslot t
$\widehat{\mathbf{u}}_m(t)$	Received tracking control signal at UAV m and timeslot t
$\mathbf{H}_m(t)$	MIMO channel matrix between the leader and the m-th follower UAV
$\delta_m(t)$	Activation indicator for communication between the leader and the m-th follower UAV
$\mathbf{A}_{mm}$	Internal transition matrix for UAV m
$\mathbf{A}$	Global transition matrix
$\mathbf{B}_m$	Actuation matrix for UAV m
$\widehat{\mathbf{B}}_m$	m-th block of the global actuation matrix
$\mathbf{\Sigma}(t)$	Global tracking error covariance
γ	Communication price or regularization constant
M	Number of follower UAVs
N_t, N_r	Number of transmit and receive antennas

II. System Model

A. Dynamic Model

A typical UAV swarm comprises $M \in \mathbb{Z}_+$ geographically distributed follower UAVs and a leader UAV, interconnected through an unreliable wireless network, as shown in Fig. 1. We assume that the leader UAV and the follower UAVs are equipped with N_t transmission antennas and N_r receiving antennas, respectively. The physical process for each m-th follower UAV is described by a set of first-order coupled equations as:

$$\mathbf{x}_m(t+1) = \mathbf{A}_{mm}\mathbf{x}_m(t) + \mathbf{B}_m\widehat{\mathbf{u}}_m(t) + \mathbf{w}(t), m \in \{1, 2, ..., M\}, \tag{1}$$

where $\mathbf{x}_m(t) = [p_{m,x}(t), p_{m,y}(t), p_{m,z}(t), v_{m,x}(t), v_{m,y}(t), v_{m,z}(t),\ a_{m,x}(t), a_{m,y}(t), a_{m,z}(t)]^T \in \mathbb{R}^{9\times1}$ is the state of the m-th follower UAV. $p_{m,n}(t) \in \mathbb{R}, v_{m,n}(t) \in \mathbb{R}$ and $a_{m,n}(t) \in \mathbb{R}$ are the position, speed, and angular speed of m-th UAV at positive n-th direction, respectively. $\mathbf{A}_{mm} \in \mathbb{R}^{9\times9}$ and $\mathbf{B}_m \in \mathbb{R}^{9\times N_r}$ are the internal transition matrix and actuation matrix for m-th follower UAV, respectively. $\widehat{\mathbf{u}}_m(t) \in \mathbb{R}^{N_r\times1}$ is the received tracking control signal at m-th follower UAV. $\mathbf{w}_m(t) \sim \mathcal{N}(0, \mathbf{W}_m)$ is the additive plant noise at m-th follower UAV with finite covariance matrix $\mathbf{W}_m \in \mathbb{S}^9$.

By aggregation, the UAV swarm follows the dynamics as:

$$\mathbf{x}(t+1) = \mathbf{A}\mathbf{x}(t) + \sum_{m=1}^{M} \widehat{\mathbf{B}}_m\widehat{\mathbf{u}}_m(t) + \widehat{\mathbf{w}}(t), \tag{2}$$

where $\mathbf{x}(t) = [\mathbf{x}_1^T(t), ..., \mathbf{x}_M^T(t)]^T \in \mathbb{R}^{9M\times1}$ is the global state for the UAV swarm, $\widehat{\mathbf{w}}(t) \sim \mathcal{N}(\mathbf{0}_{9M\times1}, \mathrm{Diag}(\mathbf{W}_1, ..., \mathbf{W}_M))$

is the global additive plant noise. $\mathbf{A} = \begin{bmatrix} \mathbf{A}_{11} & \cdots & \mathbf{A}_{1M} \\ \vdots & \vdots & \vdots \\ \mathbf{A}_{M1} & \cdots & \mathbf{A}_{MM} \end{bmatrix} \in \mathbb{R}^{9M\times 9M}$ is the global transition matrix, where $\mathbf{A}_{m,n}$ characterizes the dynamic relationship between m-th and n-th follower UAVs. $\hat{\mathbf{B}}_m = [\mathbf{0}_{N_r\times(9m-9)}, \mathbf{B}_m^T, \mathbf{0}_{N_r\times(9M-9m)}]^T \in \mathbb{R}^{9M\times N_r}$ is the m-th global actuation matrix[1].

B. Wireless Communication Model

The leader UAV observes the states $\mathbf{x}(t)$ of the follower UAVs via the depth-of-field (DOF) camera [29], and generates remote tracking control signal $\mathbf{u}_m(t) \in \mathbb{R}^{N_t\times 1}$ for each m-th follower UAV. The signal $\mathbf{u}_m(t) \in \mathbb{R}^{N_t\times 1}$ will be conveyed to the m-th follower UAV over wireless MIMO fading channels. At each m-th follower UAV, the received signal $\widehat{\mathbf{u}}_m(t) \in \mathbb{R}^{N_r\times 1}$ is given by:

$$\widehat{\mathbf{u}}_m(t) = \delta_m(t)\mathbf{H}_m(t)\mathbf{u}_m(t) + \mathbf{v}_m(t), 1 \le m \le M, \quad (3)$$

where $\delta_m(t) \in \{0,1\}$ is the communication variable that indicates the communication activity between the leader UAV and m-th follower UAV. $\mathbf{v}_m(t) \sim \mathcal{N}(\mathbf{0}_{N_r\times 1}, \mathbf{1}_{N_r})$ is the additive channel noise at m-th follower UAV. $\mathbf{H}_m(t) \in \mathbb{R}^{N_r\times N_t}$ is the wireless MIMO channel fading between the leader UAV and the m-th follower UAV. It remains constant within each timeslot and is i.i.d. over follower UAVs and timeslots, and each element of $\mathbf{H}_m(t)$ follows a Gaussian distribution with zero mean and unit variance [2].

C. Performance Metric

Let the target state $\mathbf{r}(t) \in \mathbb{R}^{9M\times 1}$ evolve according to

$$\mathbf{r}(t+1) = \mathbf{G}\mathbf{r}(t), \quad (4)$$

where $\mathbf{G} \in \mathbb{R}^{9M\times 9M}$ is the target transition matrix. The primary objective for the leader UAV is to drive the state $\mathbf{x}(t)$ to track the target profile $\mathbf{r}(t) \in \mathbb{R}^{9M\times 1}$ by designing the control signals $\{\mathbf{u}_m(t)\}$. Specifically, we have the following definition on the tracking stability of the UAV swarm.

Definition 1: (Tracking Stability of the UAV Swarm) The UAV swarm is tracking stable if

$$\limsup_{T\to\infty} \frac{1}{T}\sum_{t=1}^{T} \mathbb{E}_{\mathbf{w}(t),\{\mathbf{v}_m(t),\delta_m(t),\mathbf{H}_m(t)\}}\left\{\|\mathbf{x}(t)-\mathbf{r}(t)\|^2\right\} < \infty. \quad (5)$$

Our notion of tracking stability follows standard definitions in stochastic control and queueing theory (e.g., Section III-C in [31]), where stability is characterized by the bounded time-averaged cost $\limsup_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}[Q(t)] < \infty$. In our setting, $Q(t) = \|\mathbf{x}(t)-\mathbf{r}(t)\|^2$ measures the per-stage tracking error, and Definition 1 ensures its long-term boundedness, aligning with practical swarm tracking requirements.

[1]Throughout the paper, $\mathbf{0}_a$, $\mathbf{0}_{a\times b}$, $\mathbf{I}_a$, and $\mathbf{I}_{a\times b}$ denote an $a\times a$ matrix where all elements are zero, an $a\times b$ matrix with all zero elements, an $a\times a$ identity matrix and an $a\times b$ matrix where all elements are one, respectively.

[2] Our modeling assumes that the MIMO channel matrix $\mathbf{H}_m(t)$ follows i.i.d. Gaussian fading across time and UAVs, reflecting the block fading effect [30] and spatial separation in UAV swarms. This standard assumption ensures analytical tractability and serves as a performance baseline. In practice, spatial and temporal channel correlations may arise due to UAV mobility and shared environments. Extending the model to incorporate such correlations is a promising direction for future work.

III. Problem Formulation and Proposed Method

A. Definition and Motivation of the Lyapunov Function

Lyapunov theory offers a systematic way to analyze system stability by defining a scalar function that measures the deviation from equilibrium. If this function decreases over time, stability is ensured. In our case, we define the Lyapunov function based on the tracking error covariance $\Sigma(t) = (\mathbf{x}(t)-\mathbf{r}(t))(\mathbf{x}(t)-\mathbf{r}(t))^T$ as $L(\Sigma(t)) = \mathrm{Tr}(\Sigma(t))$. Through our design, stability of the Lyapunov function directly implies tracking stability for the UAV swarm.

B. Definition and Motivation of the Lyapunov Drift

To analyze tracking stability, we examine the one-step expected change in the Lyapunov function—known as the Lyapunov drift—defined as:

$$\Gamma(\Sigma(t)) = \mathbb{E}[L(\Sigma(t+1)) - L(\Sigma(t))|\Sigma(t)]. \quad (6)$$

A negative Lyapunov drift implies that the UAV swarm maintains bounded tracking error over time. To derive an explicit expression for the drift, we substitute the system dynamics from (2)–(4), the Lyapunov function $L(\Sigma(t))$, and the state-feedback control law $\mathbf{u}_m(t) = -\mathbf{K}_m(t)(\mathbf{x}(t)-\mathbf{r}(t))$ into the drift definition in (6). The resulting closed-form expression is presented in Theorem 1.

Theorem 1: (Lyapunov Drift Upper Bound) Let the singular value decomposition (SVD) of $\mathbf{A}$ and $\mathbf{G}$ be $\mathbf{A} = \mathbf{U}_1\Pi_1\mathbf{V}_1^T$ and $\mathbf{G} = \mathbf{U}_2\Pi_2\mathbf{V}_2^T$, respectively, where $\mathbf{U}_i \in \mathbb{R}^{9M\times 9M}$ and $\mathbf{V}_i \in \mathbb{R}^{9M\times 9M}$ are unitary matrices, and $\Pi_i = \mathrm{Diag}(\pi_{i,1},...,\pi_{i,9M}) \in \mathbb{S}^{9M}$. Define $\pi_m = \pi_{2,m}\mathbf{1}_{|\pi_{1,m}|>|\pi_{2,m}|} + \pi_{1,m}\mathbf{1}_{|\pi_{2,m}|>|\pi_{1,m}|}$, where $\mathbf{1}_{\{\mathcal{A}\}} \in \{0,1\}$ is an indicator function that equals 1 if and only if the event $\mathcal{A}$ holds true. Let $\Pi = \mathrm{Diag}(\pi_1,...,\pi_{9M}) \in \mathbb{S}^{9M}$ and $\alpha = 2\max\left\{\|\mathbf{A}\|^2, \|\mathbf{G}\|^2\right\}$. The Lyapunov drift in Eq. (6) admits the following upper bound:

$$\Gamma(\Sigma(t)) \le \mathrm{Tr}(\mathbf{W}) - \mathrm{Tr}(\Sigma(t)) + \alpha\,\mathrm{Tr}(\Sigma(t)) - \mathbb{E}[2\sum_{m=1}^{M}\mathrm{Tr}(\delta_m(t)$$
$$\mathbf{B}_m\mathbf{H}_m(t)\mathbf{K}_m(t)\Sigma(t)\Pi) + \sum_{m=1}^{M} M\delta_m(t)\,\mathrm{Tr}(\Sigma(t)(\mathbf{B}_m\mathbf{H}_m(t)$$
$$\mathbf{K}_m(t))^T(\mathbf{B}_m\mathbf{H}_m(t)\mathbf{K}_m(t)))|\Sigma(t)] + \sum_{m=1}^{M}\mathrm{Tr}(\mathbf{B}_m\mathbf{B}_m^T). \quad (7)$$

Proof: See Appendix A in the online material [32]. ■

As shown in Theorem 1, the Lyapunov drift depends on the communication variables $\{\delta_m(t)\}$ and control gains $\{\mathbf{K}_m(t)\}$. The term $\alpha\,\mathrm{Tr}(\Sigma(t)) + \mathbb{E}[\sum_{m=1}^{M}\delta_m(t)\,\mathrm{Tr}(\Sigma(t)(\mathbf{B}_m\mathbf{H}_m(t)\mathbf{K}_m(t))^T(\mathbf{B}_m\mathbf{H}_m(t)\mathbf{K}_m(t)))|\Sigma(t)]$ contributes positively to the drift and may destabilize the system, while the terms $-\mathbb{E}[2\sum_{m=1}^{M}\mathrm{Tr}(\delta_m(t)\mathbf{B}_m\mathbf{H}_m(t)\mathbf{K}_m(t)\Sigma(t)\Pi)|\Sigma(t)] - \mathrm{Tr}(\Sigma(t))$ induce negative drift and promote stability. We therefore jointly optimize $\{\delta_m(t)\}$ and $\{\mathbf{K}_m(t)\}$ to minimize the drift and enhance tracking performance.

C. Problem Formulation

We define the communication cost for each follower UAV as $\delta_m(t)(P_{on} + \gamma\,\mathrm{Tr}(\mathbf{K}_m(t)\mathbf{K}_m^T(t)))$, where P_{on} denotes a fixed activation cost, and the second term captures the dynamic power cost associated with signal transmission and control execution. Considering both the communication cost and the tracking stability objective and noting that the decision variables $\{\delta_m(t), \mathbf{K}_m(t)\}$ are decoupled across UAVs in Eq. (7), we formulate a decentralized communication-control problem for each follower UAV.

Problem 1: (Decentralized Lyapunov Optimization for the UAV Swarm) For a given $\Sigma(t)$ and $\mathbf{H}_m(t)$, the communication solution $\delta_m^*(t)$ and the control solution $\mathbf{K}_m^*(t)$ for the m-th follower UAV can be obtained by solving the problem below.

$$\begin{aligned}\min_{\delta_m(t),\mathbf{K}_m(t)} \quad & -2\delta_m(t)\operatorname{Tr}(\mathbf{H}_m(t)\mathbf{K}_m(t)\Sigma(t)\Pi) + M\delta_m(t) \\ & \operatorname{Tr}(\Sigma(t)(\mathbf{H}_m(t)\mathbf{K}_m(t))^T(\mathbf{H}_m(t)\mathbf{K}_m(t))) + \delta_m(t) \\ & (P_{on} + \gamma\operatorname{Tr}(\mathbf{K}_m(t)\mathbf{K}_m^T(t))) \\ \text{s.t.} \quad & \delta_m(t) \in \{0,1\}. \end{aligned} \tag{8}$$

where $\gamma \geq 0$ is the communication price among the UAVs and $P_{on} \geq 0$ is the activation power consumption for UAVs.

Although Problem 1 is a convex optimization problem, it is still challenging to obtain a closed-form solution due to the integer constraints.

Remark: (UAV Power Modeling Choice) Comprehensive UAV power models, such as in [33], emphasize flying power as the dominant energy cost, influenced by velocity, trajectory, and flight mode. In contrast, our model focuses on communication and control energy, which are directly affected by the proposed decision policies. While flying power is not explicitly modeled, the control gain $\mathbf{K}_m(t)$ indirectly impacts UAV dynamics and thus influences energy consumption.

D. Decentralized Semantic Solution

The structure of the objective function in Problem 1 reveals key insights into communication and control strategies. As a mixed-integer optimization involving binary variables $\delta_m(t) \in \{0,1\}$ and continuous variables $\mathbf{K}_m(t)$, it naturally lends itself to a primal decomposition approach. Fixing $\delta_m(t)$ renders the problem convex in $\mathbf{K}_m(t)$. By analyzing the optimality conditions under $\delta_m(t) = 0$ and $\delta_m(t) = 1$, we derive a closed-form and threshold-based communication policy as follows.

Consider the SVD of $\delta_m(t)\mathbf{B}_m\mathbf{H}_m(t) \in \mathbb{R}^{9M\times N_r}$ be $\delta_m(t)\mathbf{B}_m\mathbf{H}_m(t) = \mathbf{T}_{1,m}^T(t)\Xi_{1,m}(t)\mathbf{S}_{1,m}(t)$, where $\mathbf{T}_{1,m}(t) \in \mathbb{R}^{9M\times 9M}$ and $\mathbf{S}_{1,m}(t) \in \mathbb{R}^{N_r\times N_r}$ are unitary matrices, and $\Xi_{1,m}(t) \in \mathbb{R}^{9M\times N_r}$ is a rectangular matrix containing the singular values $\{\sigma_{m,1}(t), ...\sigma_{m,\text{Rank}(\delta_m(t)\mathbf{B}_m\mathbf{H}_m(t))}(t)\}$. Define $\Sigma_m(t) = \mathbf{T}_{1,m}^T(t)\Sigma(t)\mathbf{T}_{1,m}(t)$ and $\zeta_m(t) = \mathbf{T}_{1,m}^T(t)$ $\text{Diag}((\sigma_{m,1}(t))^{-2}, (\sigma_{m,2}(t))^{-2}, ..., (\sigma_{m,\text{Rank}(\delta_m(t)\mathbf{B}_m\mathbf{H}_m(t))}(t))^{-2}, 0, ..., 0)\mathbf{T}_{1,m}(t) \in \mathbb{R}^{9M\times 9M}$. The dynamic communication and control solutions to Problem 1 are then encapsulated in the following Theorem 2.

Theorem 2: (Semantic Solution) The communication and tracking control solution to Problem 1 is given as follows.

- **Inactive Mode:** If
$$P_{on} \geq \operatorname{Tr}(\Pi\Sigma_m(t)(M\Sigma(t) + \gamma\zeta_m(t))^\dagger\Sigma_m^T(t)\Pi^T), \tag{9}$$
then $\delta_m^*(t) = 0, \mathbf{K}_m^*(t) = \mathbf{0}_{9M\times N_r}$.
- **Operative Mode:** If
$$P_{on} < \operatorname{Tr}(\Pi\Sigma_m(t)(M\Sigma(t) + \gamma\zeta_m(t))^\dagger\Sigma_m^T(t)\Pi^T), \tag{10}$$
then $\delta_i^*(t) = 1$ and
$$\mathbf{K}_m^*(t) = \mathbf{V}_m^T(t)\Xi_m^\dagger(t)\mathbf{U}_m(t)\Pi\Sigma(t)(M\Sigma(t) + \gamma\zeta_m(t))^\dagger. \tag{11}$$

Proof: See Appendix B in the online material [32]. ■

The optimal solutions $\delta_m^*(t)$ and $\mathbf{K}_m^*(t)$ in Theorem 2 exhibit a decentralized semantic structure. Control signals are transmitted only when the tracking error $\|\Sigma(t)\|$ is large or the channel gain $\|\mathbf{H}_m(t)\|$ is favorable, with $\mathbf{K}_m^*(t)$ adapting accordingly. This ensures communication occurs only when the semantic utility—quantified by the expected impact on tracking under current channel conditions—outweighs the cost. While the mechanism reduces communication overhead, it is driven by a Lyapunov-based objective prioritizing stability and performance. Resource efficiency is thus an outcome of task-driven and semantically meaningful decision-making.

E. Algorithm Design

We summarize the decentralized semantic communication and tracking control algorithm in the following Algorithm 1 and Fig. 1(b).

Algorithm 1 Semantic Communication and Tracking Control over MIMO Fading Channels

Step 1 (Information Exchange): At each timeslot t, each follower UAV m broadcasts its state $\mathbf{x}_m(t) \in \mathbb{R}^{9\times 1}$ to the leader UAV. The leader broadcasts a common pilot matrix $\mathbf{T} \in \mathbb{R}^{N_t\times N_t}$ to all followers.
Step 2 (Channel Estimation and Feedback): Each follower m estimates the channel as $\hat{\mathbf{H}}_m(t)$ from the received pilot $\mathbf{Y}_m^p(t) = \mathbf{H}_m(t)\mathbf{T} + \mathbf{V}^p(t)$, where $\mathbf{V}^p(t) \sim \mathcal{N}(0, \mathbf{I}_{N_r})$, and feeds back $\hat{\mathbf{H}}_m(t)$ to the leader.
Step 3 (Semantic Policy Generation): The leader computes the optimal triggering decisions $\{\delta_m^*(t)\}$ via Theorem 2. For each $\delta_m^*(t) = 1$, it computes $\mathbf{u}_m^*(t) = -\mathbf{K}_m^*(t)\mathbf{x}(t)$ and transmits it through the MIMO channel.
Step 4 (Execution): Each follower UAV updates its state using the received signal $\hat{\mathbf{u}}_m(t)$ according to (1). Increment t and return to **Step 1**.

The total computational complexity across all M follower UAVs consists of three main components. First, performing SVD on a $9M \times N_r$ matrix incurs a cost of $O(M^2N_r^2)$ in total. Second, both communication triggering and control gain computation require $O(M^3)$ per UAV, resulting in a combined complexity of $O(M^4)$. Therefore, the overall computational complexity is $O(M^2N_r^2 + M^4)$.

F. Sufficient Condition for Tracking Stability

The sufficient condition for tracking stability can be obtained by analyzing the criteria for the negative Lyapunov drift in (7) under the proposed scheme. This is formally summarized in the following Theorem.

Theorem 3: (Sufficient Condition for Tracking Stability) Let the SVD of $\delta_m(t)\mathbf{B}_m\mathbf{H}_m(t)\mathbf{H}_m^T(t)\mathbf{B}_m^T \in \mathbb{R}^{9M\times 9M}$ be $\delta_m(t)\mathbf{B}_m\mathbf{H}_m(t)\mathbf{H}_m^T(t)\mathbf{B}_m^T = \mathbf{T}_{2,m}(t)\Xi_{2,m}(t)\mathbf{S}_{2,m}(t)$, where

$\mathbf{T}_{2,m}(t) \in \mathbb{R}^{9M\times 9M}$ and $\mathbf{T}_{2,m}(t) \in \mathbb{R}^{N_r\times N_r}$ are unitary matrices. Let $\mathbf{M}_m(t) \in \mathbb{R}^{9M\times 9M}$ be the mask matrix for $\Xi_{2,m}(t)$ satisfying $\mathbf{M}_m(t) \odot \Xi_{2,m}(t) = \Xi_{2,m}(t)$. Then, if

$$\|\mathbf{1}_{9M} - \frac{1}{M}\sum_{m=1}^{M}\mathbf{M}_m(t)\| < \frac{1}{\alpha}, \tag{12}$$

the UAV swarm is tracking stable, i.e., $\limsup_{T\to\infty}\frac{1}{T}\sum_{t=1}^{T}\mathbb{E}[\|\mathbf{x}(t)-\mathbf{r}(t)\|^2] < \infty$.

Proof: See Appendix C in the online material [32]. ■

IV. Numerical Results

A. Experiment Setup & Baselines

In this section, we evaluate the performance benefits of the proposed algorithm. Specifically, we compare our scheme against the following baselines:

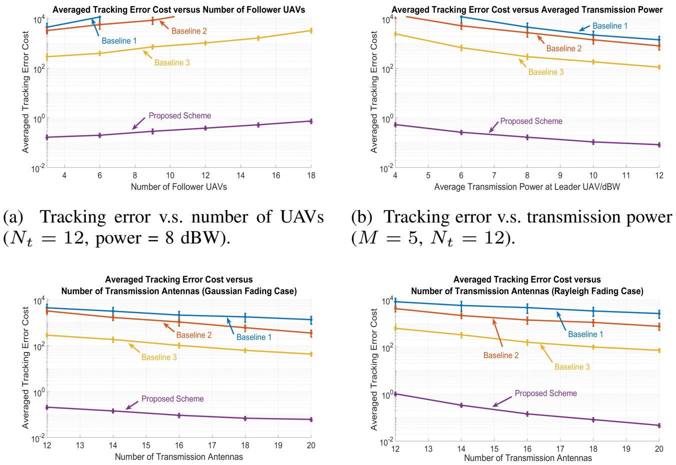
- **Baseline 1** *(Periodic Communication + PID Control):* The control signal is $\mathbf{u}_m(t) = \mathbf{K}_{m,p}(\mathbf{x}(t)-\mathbf{r}(t)) + \mathbf{K}_{m,i}\sum_{i=0}^{t}(\mathbf{x}(i)-\mathbf{r}(i)) + \mathbf{K}_{m,d}(\Delta\mathbf{x}(t)-\Delta\mathbf{r}(t))$, where the PID gains are tuned offline. Communication is triggered periodically. $\Delta(\cdot)$ denotes the time difference operator.
- **Baseline 2** *(State-Triggered Communication + PID Control):* The control law is the same as in Baseline 1, but communication is triggered only if $\|\mathbf{x}(t)-\mathbf{r}(t)-\mathbf{x}^l(t)+\mathbf{r}^l(t)\|^2 > \sigma\|\mathbf{x}(t)-\mathbf{r}(t)\|^2$, where $\mathbf{x}^l(t)$ and $\mathbf{r}^l(t)$ are the state and reference at the last transmission.
- **Baseline 3** *(State-Triggered Communication + GARE Control):* The triggering solution is the same as that in Baseline 2. The control signal is $\mathbf{u}_m(t) = \mathbf{K}_{m,g}(\mathbf{x}(t)-\mathbf{r}(t))$, where $\mathbf{K}_{m,g}$ is an offline solution to the GARE under static channels $\mathbf{H}_m(t) = \mathbf{1}_{N_r\times N_t}$.

The three baselines illustrate a clear performance progression: Baseline 1 lacks adaptation in both communication and control; Baseline 2 improves communication via adaptive triggering but uses fixed control; Baseline 3 further enhances control with a GARE controller, yet both communication and control remain channel-insensitive.

Let $\mathbf{A}_{mm} \in \mathbb{R}^{9\times 9}$ and $\mathbf{B}_m \in \mathbb{R}^{9\times 9}$ be randomly drawn from a standard Gaussian distribution. For any $m \in \{1,\dots,M\}$, we set $\mathbf{A}_{m,n} = \mathbf{A}_{mm}$ if $n = (m \bmod M)+1$, and $\mathbf{A}_{m,n} = \mathbf{0}_9$ otherwise. The process noise $\mathbf{w}_m(t)$ follows $\mathcal{N}(\mathbf{0}_9, 10^{-5}\mathbf{I}_9)$. $\sigma_m = m$, and the periodic triggering interval is $\lceil M/2\rceil$. Initial states are set as $\mathbf{x}(0) = [1,\dots,1]^T$ and $\mathbf{r}(0) = [100,\dots,100]^T$. $P_{on} = \gamma = 0.5$. The global target matrix $\mathbf{G}_k \in \mathbb{R}^{9M\times 9M}$ alternates periodically: $\mathbf{G}(t) = 1.05\,\mathbf{I}_{9M}$ if $t \bmod 6 < 3$, and $0.95\,\mathbf{I}_{9M}$ otherwise.

B. Performance Comparison & Analysis

1) Impact of Number of UAVs: Fig. 2(a) shows that tracking becomes increasingly challenging with more follower UAVs. Our proposed method achieves the lowest averaged tracking error cost in (5) by adapting to both dynamics and channel conditions. In contrast, Baseline 1 uses periodic communication and fixed PID control, ignoring state and channel variations. Baseline 2 introduces state-triggered communication but retains fixed control. Baseline 3 improves control via GARE-based gains but remains channel-unaware. While performance improves from Baseline 1 to 3, all are outperformed by our fully adaptive scheme.



(a) Tracking error v.s. number of UAVs (N_t = 12, power = 8 dBW).

(b) Tracking error v.s. transmission power ($M = 5$, $N_t = 12$).

(c) Tracking error v.s. number of antennas ($M = 5$, 8 dBW).

(d) Tracking error v.s. number of antennas (Rayleigh, $M = 5$, 8 dBW).

Fig. 2: Averaged tracking error cost under different UAV system parameters. Each point averages the tracking cost over $T = 10^4$ timeslots and 100 Monte Carlo runs. Error bars denote the sample standard deviation, indicating the statistical variation (68.27% confidence).

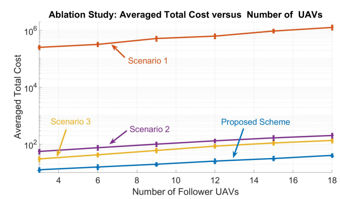


Fig. 3: Ablation study on total cost v.s. number of follower UAVs. All simulation configurations are consistent with those used in Fig. 2(a).

2) Impact of Averaged Transmission Power at leader UAV: Fig. 2(b) shows the average tracking error versus the leader UAV's transmission power. As power increases, all schemes benefit from improved signal to noise ratios (SNR) and tracking performance. Notably, our proposed method achieves stable tracking with significantly lower power, highlighting its superior efficiency compared to the baselines.

3) Impact of Number of Transmission Antennas: Fig. 2(c) presents the average tracking error cost in (5) plotted against the number of transmission antennas N_t. The results indicate that an increase in N_t leads to a reduction in tracking error cost for all schemes, as the expanded communication resources enhance the overall system performance. Our proposed scheme excels over the baseline schemes by dynamically adjusting the communication and control strategies in response to real-time plant and channel state realizations.

4) Robustness Performance: Fig. 2(d) presents the average tracking error under Rayleigh fading channels as a function of the number of transmit antennas N_t, where each entry of $\mathbf{H}_m(t)$ follows a Rayleigh distribution with scale 3. Our scheme consistently outperforms all baselines, demonstrating strong robustness to non-Gaussian fading. This advantage stems from its adaptive design, in which both communication triggering and control gains dynamically respond to instantaneous channel conditions. In contrast, baseline methods rely on fixed policies and exhibit degraded performance under time-varying channels.

5) Ablation Study: To evaluate key design choices, we compare the total cost $\limsup_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1}(\mathbb{E}[\|\mathbf{x}(t)-\mathbf{r}(t)\|^2] + \sum_m \mathbb{E}[\delta_m(t)(P_{\text{on}}+\gamma\,\text{Tr}(\mathbf{K}_m(t)\mathbf{K}_m^\top(t)))])$ under four variants: (i) without MIMO modeling (fixed $\mathbf{H}_m$), (ii) without semantic triggering (always transmit), (iii) triggered only by state error (ignoring channel), and (iv) the proposed scheme. Fig. 3 demonstrates that removing either component results in a higher total cost—stemming from system instability when MIMO modeling is omitted, or from inefficient communication when semantic triggering or channel-awareness is absent. This underscores the advantage of jointly optimizing control and communication.

V. Conclusions

In this work, we propose a novel framework for decentralized semantic communication and cooperative tracking control in UAV swarms over wireless MIMO fading channels. Unlike prior studies that assume static or idealized channels, we formulate a power-aware drift-plus-penalty problem that jointly captures tracking performance and communication cost, and derive a closed-form, threshold-based solution that preserves a semantic structure—communication and control decisions are driven by task relevance and local channel conditions. Furthermore, we establish a closed-form Lyapunov-based stability condition, offering analytical performance guarantees. Numerical evaluations show that our method significantly outperforms existing approaches in both accuracy and efficiency. Future work will extend the framework to more realistic scenarios with non-iid Gaussian fading, partial CSI, dynamic uncertainties, and explicit flying power models, enabling a more comprehensive evaluation of the proposed semantic-aware control strategy in practical UAV swarm applications.

References

[1] Y. Chen, B. Hao, T. Yu, F. Niu, Y. Shi, and M. Sun, "Fully distributed prescribed-time optimization with time-varying cost function," *IEEE Trans. Veh. Technol.*, vol. 74, no. 3, pp. 3627–3637, 2025.

[2] S. Qian, J. Xu, Y. Niu, and T. Jiao, "Iterative learning cascade trajectory tracking control for quadrotor-uavs with finite-frequency disturbances," *IEEE Trans. Veh. Technol.*, vol. 74, no. 4, pp. 5624–5636, 2025.

[3] M.-T. Tran, T. Huynh, S. Chakir, D.-H. Lee, and Y.-B. Kim, "Angular motion control design for a single ducted-fan UAV using robust adaptive pole-placement scheme in presence of bounded disturbances," *J. Mech. Sci. Technol.*, vol. 36, no. 4, pp. 2031–2041, 2022.

[4] Y.-H. Su, P. Bhowmick, and A. Lanzon, "A fixed-time formation-containment control scheme for multi-agent systems with motion planning: Applications to quadcopter UAVs," *IEEE Trans. Veh. Technol.*, vol. 73, no. 7, pp. 9495–9507, 2024.

[5] E. Bertran and A. Sànchez-Cerdà, "On the tradeoff between electrical power consumption and flight performance in fixed-wing UAV autopilots," *IEEE Trans. Veh. Technol.*, vol. 65, no. 11, pp. 8832–8840, 2016.

[6] Z.-Y. Lv, S. Li, Y. Wu, and Q.-G. Wang, "Adaptive control for a quadrotor transporting a cable-suspended payload with unknown mass in the presence of rotor downwash," *IEEE Trans. Veh. Technol.*, vol. 70, no. 9, pp. 8505–8518, 2021.

[7] M. R. Cohen, K. Abdulrahim, and J. R. Forbes, "Finite-horizon lqr control of quadrotors on $SE_2(3)$," *IEEE Rob. Autom. Lett.*, vol. 5, no. 4, pp. 5748–5755, 2020.

[8] Y. Luo, F. Tang, H. Zhang, and D. Yang, "Synchronous position-attitude loop regulation-based distributed optimal trajectory tracking control for multi-UAVs formation with external disturbances," *IEEE Trans. Syst. Man Cybern. Syst.*, vol. 54, no. 12, pp. 7445–7456, 2024.

[9] S. Chen, Y. Kang, J. Di, and Y. Cao, "Graph convolutional flocking control for unmanned aerial vehicles with packet dropouts," *IEEE Trans. Ind. Electron.*, vol. 71, no. 11, pp. 14 401–14 409, 2024.

[10] L. Wang, H. Li, and Y. Jiang, "Adaptive-opportunistic aloha: A media access control protocol for unmanned aerial vehicle–wireless sensor network systems," *Int. J. Distrib. Sens. Netw.*, vol. 12, no. 8, 2016.

[11] S. James, R. Raheb, and A. Hudak, "Impact of packet loss to the motion of autonomous UAV swarms," in *AIAA/IEEE Digital Avionics Systems Conf. (DASC)*, San Antonio, TX, USA, 2020, pp. 1–9.

[12] S.-M. Lee, M. Shin, and H. Son, "Robust predictor-based control for multirotor UAV with various time delays," *IEEE Trans. Ind. Electron.*, vol. 70, no. 8, pp. 8151–8162, 2022.

[13] K. Liu, R. Wang, S. Zheng, S. Dong, and G. Sun, "Fixed-time disturbance observer-based robust fault-tolerant tracking control for uncertain quadrotor UAV subject to input delay," *Nonlinear Dyn.*, vol. 107, no. 3, pp. 2363–2390, 2022.

[14] J. Wu, C. Luo, G. Min, and S. McClean, "Formation control algorithms for multi-UAV systems with unstable topologies and hybrid delays," *IEEE Trans. Veh. Technol.*, vol. 73, no. 9, pp. 12 358–12 369, 2024.

[15] Y. Zeng, R. Zhang, and T. J. Lim, "Throughput maximization for UAV-enabled mobile relaying systems," *IEEE Trans. Commun.*, vol. 64, no. 12, pp. 4983–4996, 2016.

[16] J. Lyu, Y. Zeng, and R. Zhang, "Cyclical multiple access in UAV-aided communications: A throughput-delay tradeoff," *IEEE Wireless Commun. Lett.*, vol. 5, no. 6, pp. 600–603, 2016.

[17] Z. Xiao, P. Xia, and X.-G. Xia, "Enabling UAV cellular with millimeter-wave communication: Potentials and approaches," *IEEE Commun. Mag.*, vol. 54, no. 5, pp. 66–73, 2016.

[18] Q. Wu, Y. Zeng, and R. Zhang, "Joint trajectory and communication design for multi-UAV enabled wireless networks," *IEEE Trans. Wireless Commun.*, vol. 17, no. 3, pp. 2109–2121, 2018.

[19] H. Huang, C. Hu, J. Zhu, M. Wu, and R. Malekian, "Stochastic task scheduling in UAV-based intelligent on-demand meal delivery system," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 8, pp. 13 040–13 054, 2021.

[20] L. Wei, M. Chen, and T. Li, "Dynamic event-triggered cooperative formation control for UAVs subject to time-varying disturbances," *IET Control Theory Appl.*, vol. 14, no. 17, pp. 2514–2525, 2020.

[21] B. Zhang, X. Sun, M. Lv, and S. Liu, "Distributed coordinated control for fixed-wing UAVs with dynamic event-triggered communication," *IEEE Trans. Veh. Technol.*, vol. 71, no. 5, pp. 4665–4676, 2022.

[22] Z. Wu, Y. Wang, A. Zhang, J. Xiong, and M. Xie, "QoS-dependent event-triggered control for UAVs on cognitive radio networks subject to deception attacks," *IEEE Trans. Veh. Technol.*, vol. 72, no. 9, pp. 11 389–11 400, 2023.

[23] S. Liu, B. Jiang, Z. Mao, and Y. Zhang, "Decentralized adaptive event-triggered fault-tolerant synchronization tracking control of multiple UAVs and UGVs with prescribed performance," *IEEE Trans. Veh. Technol.*, vol. 73, no. 7, pp. 9656–9665, 2024.

[24] Y. Shu, C. Liu, L. Xu, Y. Jin, G. Xu, K. Li, and H. Chen, "Event-triggered asynchronous distributed mpc for multi-quadrotor systems with communication delays," *Int. J. Robust Nonlinear Control*, vol. 34, no. 16, pp. 10 891–10 910, 2024.

[25] M. Kountouris and N. Pappas, "Semantics-empowered communication for networked intelligent systems," *IEEE Commun. Mag.*, vol. 59, no. 6, pp. 96–102, 2021.

[26] S. R. Pokhrel and J. Choi, "Understand-before-talk (UBT): A semantic communication approach to 6G networks," *IEEE Trans. Veh. Technol.*, vol. 72, no. 3, pp. 3544–3556, 2022.

[27] S. Guo, Y. Wang, S. Li, and N. Saeed, "Semantic importance-aware communications using pre-trained language models," *IEEE Commun. Lett.*, vol. 27, no. 9, pp. 2328–2332, 2023.

[28] M. Tang, S. Cai, and V. K. Lau, "Online system identification and control for linear systems with multiagent controllers over wireless interference channels," *IEEE Trans. Autom. Control*, vol. 68, no. 10, pp. 6020–6035, 2022.

[29] G. Gallego, J. E. Lund, E. Mueggler, H. Rebecq, T. Delbruck, and D. Scaramuzza, "Event-based, 6-dof camera tracking from photometric depth maps," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 40, no. 10, pp. 2402–2412, 2017.

[30] Y. Xi, A. Burr, J. Wei, and D. Grace, "A general upper bound to evaluate packet error rate over quasi-static fading channels," *IEEE Trans. Wireless Commun.*, vol. 10, no. 5, pp. 1373–1377, 2011.

[31] M. J. Neely, "Delay-based network utility maximization," *IEEE/ACM Trans. Netw.*, vol. 21, no. 1, pp. 41–54, 2012.

[32] M. Tang, C. Feng, and T. Q. Quek, "Supplementary materials of decentralized semantic communication and cooperative tracking control for a UAV swarm," *arXiv preprint arXiv:2411.06136*, 2024.

[33] Y. Zeng, Q. Wu, and R. Zhang, "Accessing from the sky: A tutorial on UAV communications for 5G and beyond," *Proc. IEEE*, vol. 107, no. 12, pp. 2327–2375, 2019.