Decentralized UAV Swarm Interception under Limited Communication with Parameter Optimization [⋆]

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Abstract

This paper studies decentralized interception of moving aerial targets by a UAV swarm under limited communication. Each UAV operates autonomously using local sensory information without centralized coordination. Several decentralized interception algorithms are evaluated within a unified simulation framework using formal metrics of efficiency, safety, and swarm coherence. Systematic parameter optimization is applied to improve performance. The results show that parameter tuning significantly enhances interception efficiency and safety, especially for algorithms with explicit local inter-agent interactions. The experiments are conducted in a controlled simulation environment involving multiple interceptor UAVs and moving targets operating under limited sensing and communication conditions. The obtained results demonstrate that systematic parameter optimization enables a more balanced trade-off between interception efficiency, swarm coherence, and safe inter-agent interaction.

Keywords

decentralized control, UAV swarm, target interception, parameter optimization

1. Introduction

Unmanned aerial vehicles (UAVs) are widely employed in monitoring, surveillance, and security-related tasks, while the use of swarm-based systems enables improved robustness and responsiveness through the distribution of functions among multiple agents. One of the most demanding application scenarios is the interception of moving aerial targets, in which a swarm must simultaneously ensure rapid convergence to the targets, coordinated group motion, and the maintenance of safe inter-agent distances.

In real-world operating conditions, communication channels between UAVs may be limited, unstable, or degraded due to interference, packet losses, or bandwidth constraints. Under such circumstances, control architectures that rely on continuous information exchange or centralized coordination rapidly lose effectiveness. This motivates the use of decentralized control strategies in which each agent operates autonomously based on locally available information and nearest-neighbor interactions, enabling scalability and robustness to communication failures [3, 13].

In this work, the problem is formulated as a decentralized control problem for interceptor UAVs: at each time step, each UAV must generate a motion control command based on its own state and locally available information about the targets, with the objective of minimizing interception time and overall swarm motion costs, while simultaneously maintaining safe inter-agent distances and coherent group behavior. An additional challenge arises from the fact that the performance of even well-established decentralized control laws strongly depends on the choice of

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their parameters; however, in many existing studies these parameters are selected heuristically, which complicates reproducibility and conceals the true performance potential of the algorithms.

The objective of this work is to perform a comparative evaluation of a set of decentralized interception algorithms within a unified simulation environment with limited communication and to improve their performance through parameter optimization with respect to formalized metrics of efficiency, safety, and swarm coherence.

2. Relevance and challenges of decentralized swarm control

The relevance of decentralized swarm control for UAV interception tasks is driven by the growing complexity and uncertainty of real-world operational environments. Interception of moving aerial targets imposes strict real-time constraints, dynamic target behavior, and safety requirements, which significantly limit the applicability of centralized or communication-intensive control architectures. Under such conditions, decentralized control strategies, in which each agent operates autonomously based on locally available information, become not only advantageous but often necessary for practical deployment [1, 2].

A defining feature of decentralized control is the absence of a global coordinator and the reliance on local sensing and limited communication. Each UAV independently computes control actions using its own state and partial observations of the environment, such as relative target positions or nearby agents detected by onboard sensors. This paradigm enhances scalability and robustness to communication failures and packet losses, which are common in contested or cluttered environments, but simultaneously complicates the achievement of coordinated group behavior [3].

The core challenge of decentralized swarm interception lies in balancing individual autonomy with collective performance. While decentralized approaches improve resilience to communication degradation, they inherently lack global situational awareness, which makes it difficult to enforce swarm-level objectives such as efficient spatial distribution, collision avoidance, and coordinated convergence toward targets. As a consequence of limited global awareness and purely local decision-making, decentralized interception algorithms often exhibit emergent behaviors that are highly sensitive to initial conditions and control parameters. Small variations in interaction gains or pursuit aggressiveness may result in qualitatively different swarm dynamics, including fragmentation, oscillatory motion, or congestion effects [4, 5, 15].

An additional and critical challenge arises from the parameterization of decentralized control laws. Parameters governing pursuit aggressiveness, interaction strength, and safety margins have a direct impact on interception efficiency, stability, and swarm coherence. However, in many existing studies these parameters are selected heuristically or fixed a priori, which limits reproducibility and obscures the true performance potential of the algorithms. This creates a gap between theoretical feasibility and practical effectiveness of decentralized swarm interception methods [6].

3. Decentralized control problem for swarm interception

Consider a swarm of interceptor unmanned aerial vehicles operating in a two-dimensional environment and tasked with intercepting one or more moving aerial targets. Each interceptor is modeled as an autonomous agent that evolves according to its own motion dynamics and is capable of obtaining local sensory information about the environment. The global objective of the swarm is to intercept the targets within minimal time while maintaining safe inter-agent distances and coherent collective motion.

The control architecture is assumed to be decentralized. At each discrete time step, each interceptor generates its control command independently based solely on its own state and locally available observations. These observations may include the relative position and velocity of nearby targets as well as limited information about neighboring interceptors within a finite sensing or communication radius. No centralized coordinator or global state information is available to the agents, and direct communication between UAVs is assumed to be limited, unreliable, or completely absent. Instead, each interceptor relies on local sensing and nearest-neighbor observations, which is consistent with graph-based decentralized control formulations under communication constraints [3, 7, 13].

Let the state of interceptor iii at time ttt be defined by its position and velocity. The control input corresponds to a motion command that determines the direction and magnitude of the interceptor's movement subject to kinematic constraints. The target dynamics are assumed to be independent of the swarm and may involve unknown or time-varying maneuvers. An interception event is considered successful when an interceptor reaches a predefined proximity threshold relative to a target.

Under these assumptions, the decentralized interception problem can be formulated as a multi-objective control problem. Each interceptor must pursue the targets efficiently while simultaneously avoiding unsafe proximity to other agents and preserving overall swarm coherence. These objectives are often conflicting: aggressive pursuit strategies may reduce interception time but increase collision risk, whereas conservative interaction rules improve safety at the expense of efficiency [4, 5].

A further difficulty arises from the parameterized nature of decentralized control laws. Algorithms such as leader–follower pursuit, proportional navigation, artificial potential fields, and local interaction–based control rely on parameters that govern pursuit aggressiveness, interaction strength, and safety margins. The values of these parameters have a significant impact on the resulting swarm behavior and overall mission performance. In most existing studies, parameters are chosen heuristically or fixed across scenarios, which limits adaptability and prevents systematic performance comparison [6, 8].

Therefore, the problem addressed in this work is defined as follows: given a set of decentralized interception algorithms and a common simulation environment with limited communication, determine control parameter values that optimize swarm performance with respect to formally defined metrics of interception efficiency, safety, and coherence. This formulation provides the foundation for the comparative analysis and parameter optimization framework presented in the subsequent sections.

4. Decentralized swarm control algorithms

Decentralized control constitutes a fundamental paradigm for swarm-based unmanned aerial vehicle (UAV) systems, particularly in scenarios where centralized coordination or reliable inter-agent communication cannot be guaranteed. In decentralized architectures, each agent computes its control actions autonomously based on locally available information, which enables scalability, robustness to single-point failures, and applicability in communication-degraded environments [1, 2]. These properties make decentralized algorithms especially suitable for time-critical missions such as interception of moving aerial targets.

In the context of swarm interception, decentralized control algorithms are typically designed to generate pursuit behaviors using local sensing of targets and nearby agents, while implicitly addressing spatial dispersion and collision avoidance. Unlike centralized task-allocation or consensus-based approaches, decentralized methods do not require global knowledge of the swarm state and can operate solely on onboard measurements, such as relative positions and velocities obtained via radar or vision sensors [3].

Existing decentralized swarm control approaches differ in their principles of local decision-making, interaction mechanisms, and parameterization. Nevertheless, most of them can be interpreted as local control laws that collectively give rise to emergent swarm behavior [4]. The following subsections review the main decentralized algorithms commonly employed for pursuit and interception tasks, serving as baseline methods for subsequent analysis and comparison.

4.1. Leader–follower pursuit

Leader–follower pursuit represents a class of decentralized control strategies in which agents implicitly assume leader and follower roles based on local interaction rules rather than explicit communication or centralized coordination. In such approaches, a subset of agents effectively acts as leaders by directly pursuing the target, while the remaining agents follow the induced motion patterns through local decision-making mechanisms. This paradigm has been widely studied in the context of decentralized multi-agent control and pursuit–evasion problems [5].

In swarm interception scenarios, the leader–follower strategy is commonly implemented by allowing each interceptor to generate a pursuit command toward a locally selected target or reference point derived from target motion. A lead point prediction is often employed to anticipate the future position of the target and improve interception efficiency. Importantly, leader–follower roles emerge implicitly from spatial configuration and relative motion, without explicit assignment or negotiation among agents, which preserves the fully decentralized nature of the algorithm [6].

Despite its conceptual simplicity and low computational complexity, leader–follower pursuit exhibits inherent limitations in multi-agent interception tasks. Since agents make decisions independently, multiple interceptors may converge toward the same target or spatial region, increasing the risk of congestion and unsafe proximity. Moreover, the performance of the algorithm is highly sensitive to the choice of lead time and motion scaling parameters, which are typically selected heuristically in existing studies [7]. These properties make leader–follower pursuit a representative baseline method for evaluating the impact of parameter tuning and safety mechanisms in decentralized swarm interception.

Algorithm 1. Leader–follower decentralized pursuit

Input:

Interceptor position p_i, velocity v_i;
locally observed target position p_t, target velocity v_t;
lead time parameter T_{lead};
maximum speed v_{max}.

Output:

Control command u_i.

Step 1.

Target lead point estimation:

$$p_{lead} = p_t + T_{lead} \cdot v_t.$$

Step 2.

Desired pursuit direction:

$$d_i = p_{lead} - p_i.$$

Step 3.

Control normalization:

$$u_i = v_{max} \frac{di}{||di||}.$$

Step 4.

Apply control command to interceptor dynamics.

4.2. Proportional navigation

Proportional navigation (PN) is a classical guidance law originally developed for missile guidance and later adopted in pursuit–evasion and interception problems. The fundamental principle of PN is to generate control commands proportional to the rate of change of the line-of-sight (LOS) angle between the interceptor and the target, which ensures asymptotic convergence under mild assumptions on target motion [16, 17].

In decentralized swarm interception scenarios, proportional navigation can be implemented independently by each interceptor using only local measurements of the relative position and velocity of the target. No explicit coordination or information exchange between agents is required, which makes PN inherently compatible with communication-limited environments. Each interceptor computes its own guidance command based solely on the locally observed LOS dynamics, resulting in decentralized yet simultaneous pursuit of the target by multiple agents [9].

However, when applied to swarm interception, proportional navigation exhibits several limitations. Since PN does not explicitly account for the presence of other interceptors, it may lead to convergence of multiple agents toward similar trajectories or interception points, increasing the risk of close encounters or collisions. Moreover, the performance of PN is strongly influenced by the choice of the navigation constant, which is typically fixed a priori and selected heuristically. These characteristics make PN a suitable reference algorithm for evaluating the effectiveness of additional coordination mechanisms and parameter optimization strategies in decentralized swarm interception [10].

Algorithm 2. Proportional navigation–based decentralized interception

Input:

interceptor position p_i;
interceptor velocity v_i;
target position p_t;
target velocity v_t;
navigation constant N;
relative distance r_{it}.

Output:

Control command u_i.

Step 1.

Compute the relative position vector between interceptor and target:

$$r_{it} = p_t - p_i.$$

Step 2.

Determine the line-of-sight (LOS) angle λ as the angle of vector r_{it}.

Step 3.

Estimate the rate of change of the LOS angle:

$$\dot{\lambda} = \frac{d\lambda}{dt}.$$

Step 4.

Compute the lateral acceleration command according to the proportional navigation law:

$$a_i = N \cdot V_c \cdot \dot{\lambda},$$

where V_c denotes the closing velocity between the interceptor and the target.

Step 5.

Convert the acceleration command into a control vector u_i consistent with the interceptor dynamics.

Step 6.

Apply the control command u_i to the interceptor.

4.3. Local interaction–based swarm control

Local interaction–based swarm control represents a class of decentralized approaches in which the global behavior of the swarm emerges from simple local interaction rules between neighboring agents. These methods are inspired by natural collective systems, such as bird flocks or fish schools, where coordination is achieved without centralized control or global communication. In engineering applications, local interaction–based control has been widely studied as a scalable and robust solution for multi-agent coordination under communication constraints [1,2,4].

In the context of swarm interception, local interaction–based control relies on each interceptor adjusting its motion based on the relative positions and velocities of nearby agents and the target. Typical interaction rules include attraction toward the target, alignment with neighboring agents, and separation to maintain safe inter-agent distances. All computations are performed locally using information available within a limited sensing or communication radius, which makes these approaches particularly suitable for environments with restricted or unreliable communication links [15].

Compared to classical pursuit laws such as proportional navigation or leader–follower strategies, local interaction–based swarm control explicitly accounts for inter-agent interactions. This allows the swarm to maintain coherent spatial structures and reduce congestion during interception maneuvers. However, the resulting collective behavior is highly dependent on the tuning of interaction gains and neighborhood radii. Inappropriate parameter choices may lead to swarm fragmentation, oscillatory motion, or loss of interception efficiency. Consequently, local interaction–based methods are commonly used as a foundation for studying adaptive and optimized parameter selection in decentralized swarm systems [6].

Algorithm 3. Local interaction–based decentralized swarm control

```
Input:
    interceptor position $p_i$;
    interceptor velocity $v_i$;
    target position $p_t$;
    set of neighboring interceptors $N_i$;
    attraction gain $k_t$;
    alignment gain $k_a$;
    separation gain $k_s$;
    interaction radius $R$;
    maximum speed $v_{max}$.
Output:
Control command $u_i$.
Step 1.
Identify the set of neighboring interceptors $j \in N_i$ such that $||p_i - p_j|| \leq R$.
Step 2.
Compute the attraction component toward the target:
    $F_t = k_t \cdot (p_t - p_i)$.
Step 3.
Compute the alignment component based on neighboring velocities:
    $F_a = k_a \cdot \frac{1}{|N_i|} \cdot \sum_{j \in N_i} v_j - v_i$.
Step 4.
Compute the separation component to avoid close proximity:
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    $F_s = k_s \cdot \sum_{j \in N_i, \|p_i - p_j\| < R} \frac{p_i - p_j}{\|p_i - p_j\|}.$
Step 5.
Compute the resultant interaction force:
    $F_i = F_t + F_a + F_s.$
Step 6.
Normalize and scale the control command:
    $u_i = v_{max} \cdot \frac{F_i}{\|F_i\|}.$
Step 7.
Apply the control command $u_i$ to the interceptor dynamics.
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4.4. Artificial potential field

Artificial potential field (APF) methods represent one of the earliest and most widely used approaches for decentralized motion control in robotics. In this framework, navigation objectives and collision avoidance constraints are encoded as virtual attractive and repulsive potential functions, whose gradients generate control commands in real time. Due to their local and continuous nature, APF-based methods are well suited for decentralized implementations under limited communication conditions [14].

In swarm interception scenarios, artificial potential fields are commonly employed to simultaneously address target pursuit and inter-agent collision avoidance. Each interceptor constructs its own potential field based on locally observed information, such as the relative position of the target and neighboring agents. The attractive potential is typically defined with respect to the target position, while repulsive potentials are generated around nearby interceptors to enforce a minimum safety distance. As a result, coordinated swarm behavior emerges implicitly from local interactions without the need for centralized control or explicit communication [14].

Despite their conceptual simplicity and computational efficiency, APF-based approaches exhibit several well-known limitations. In particular, the superposition of multiple potential components may lead to the existence of local minima, in which agents become trapped and fail to reach the target. Moreover, the performance and stability of the swarm are highly sensitive to the choice of potential field parameters, such as attraction and repulsion gains and interaction radii, which are often selected heuristically. These drawbacks motivate the use of APF as a baseline method for studying the influence of parameter tuning and optimization in decentralized swarm interception tasks [14].

Algorithm 4. Artificial potential field–based decentralized control

```
Input:
    interceptor position $p_i$;
    target position $p_t$;
    set of neighboring interceptors $N_i$;
    attractive gain $k_{att}$;
    repulsive gain $k_{rep}$;
    safety distance $d_{safe}$;
    maximum speed $v_{max}$.
Output:
Control command $u_i$.
Step 1.
Compute the attractive force toward the target:
```

$$F_{att} = k_{att} \cdot (p_t - p_i).$$

Step 2.
Initialize the total repulsive force:

$$F_{rep} = 0.$$

Step 3.
For each neighboring interceptor $j \in N_i$, if $\|p_i - p_j\| < d_{safe}$, compute the repulsive contribution:

$$F_{rep} = F_{rep} + k_{rep} \cdot \left(\frac{1}{\|p_i - p_j\|} - \frac{1}{d_{safe}} \right) \cdot \frac{p_i - p_j}{\|p_i - p_j\|}.$$

Step 4.
Compute the resultant force acting on the interceptor:

$$F_i = F_{att} + F_{rep}.$$

Step 5.
Normalize the resultant force and scale it according to the maximum speed:

$$u_i = v_{max} \cdot \frac{F_i}{\|F_i\|}.$$

Step 6.
Apply the control command u_i to the interceptor dynamics.

5. Metrics

To ensure a fair, consistent, and reproducible comparison of decentralized interception algorithms, a unified set of performance metrics is employed in this study. All metrics are computed directly during simulation and are designed to jointly capture swarm motion coherence, safety of inter-agent interaction, and mission-level interception efficiency. The use of a common metric set allows objective evaluation of different control strategies under identical operating conditions.

One of the fundamental indicators of collective swarm behavior is swarm polarization, which reflects the degree of alignment in the motion directions of the UAVs. It is defined as

$$\Phi = \frac{1}{N} \cdot \left\| \left(\sum_{i=1}^{N} \frac{v_i}{\|v_i\|} \right) \right\|, \tag{1}$$

where N denotes the number of UAVs in the swarm, v_i is the velocity vector of the i-th UAV, and $\|v_i\|$ is its speed magnitude. Polarization quantifies the level of directional coherence within the swarm. A value $\Phi = 1$ corresponds to perfectly aligned motion of all agents in the same direction, whereas values close to zero indicate disordered or uncoordinated behavior. This metric is used to assess how effectively a given algorithm promotes organized collective motion during interception.

Safety is a critical aspect of decentralized swarm operation; therefore, distance-based metrics are employed to characterize inter-agent separation. The minimum inter-agent distance is defined as

$$d_{min} = \min_{i \neq j} \|p_i - p_j\|, \tag{2}$$

where p_i and p_j denote the positions of the i-th and j-th UAVs, respectively. A decrease of this metric below a predefined threshold indicates an increased risk of collision and insufficient coordination among agents.

For a more detailed safety assessment, the number of collisions is computed by counting all violations of the minimum safe distance during the simulation:

$$N_{coll} = \sum_{t} \sum_{i<j} 1_{\|p_i(t) - p_j(t)\| < d_{safe}}, \tag{3}$$

where d_{safe} is the minimum allowable safe distance and $1_{\langle \cdot \rangle}$ is the indicator function that equals 1 if the condition inside the braces is satisfied and 0 otherwise. This metric is particularly important for evaluating the practical applicability of decentralized algorithms in dense swarm configurations and under limited communication conditions.

In addition to coherence and safety, interception efficiency metrics are used to evaluate mission performance. These include the total and average interception time of targets, which characterize algorithm responsiveness, as well as the cumulative distance traveled by the UAVs, which reflects overall motion and energy expenditure of the swarm. These metrics are especially relevant in the context of parameter optimization, as even small changes in control gains may significantly affect both interception speed and interaction intensity among agents.

The combined use of the proposed metrics enables a comprehensive quantitative comparison of decentralized interception algorithms and provides a reliable basis for analyzing trade-offs between efficiency, safety, and swarm coherence.

6. Proposed solution and experimental setup

The proposed solution is based on a unified evaluation and optimization framework for decentralized swarm interception algorithms operating under limited communication conditions. Rather than introducing a new control law, this work focuses on revealing and improving the practical performance potential of well-established decentralized interception strategies through systematic parameter optimization and fair comparative analysis. This approach allows the intrinsic properties of each algorithm to be assessed under identical operating assumptions and constraints.

The key idea of the proposed framework is to treat each decentralized control algorithm as a parameterized control law and to optimize its parameters with respect to a common set of formally defined performance metrics. These metrics jointly capture interception efficiency, swarm coherence, and safety of inter-agent interaction. By optimizing parameters within the same simulation environment, the influence of algorithmic structure can be separated from the influence of parameter selection, which is often overlooked in existing studies.

The optimization process is performed in a fully simulation-based manner. For a given set of control parameters, multiple interception scenarios are simulated, and the resulting swarm trajectories are evaluated using the metrics defined in the previous section. The obtained metric values are then aggregated into an objective function reflecting the desired trade-off between efficiency, safety, and coherence. This objective function serves as the basis for parameter tuning and comparative performance assessment of different decentralized algorithms.

The experimental setup considers a two-dimensional bounded environment populated by a swarm of interceptor UAVs and one or more moving aerial targets. Each interceptor is modeled as a kinematically constrained agent with bounded speed and acceleration. Target motion follows predefined dynamic profiles and is independent of the swarm behavior. An interception is considered successful when the distance between an interceptor and a target falls below a predefined capture radius.

Communication between UAVs is assumed to be limited or absent. Each interceptor relies primarily on local sensory information, including its own state, the relative position and velocity of nearby targets, and the states of neighboring interceptors within a finite sensing radius. No global coordination, centralized planning, or explicit message exchange is employed during the interception process. This setup reflects realistic operating conditions in which communication bandwidth is constrained or unreliable.

All algorithms are evaluated under identical initial conditions, environmental constraints, and target trajectories to ensure a fair comparison. The same simulation time horizon, safety thresholds, and sensing ranges are used across all experiments. Such a unified experimental protocol ensures that observed performance differences can be attributed to algorithmic characteristics and parameter choices rather than to scenario-specific variations.

To ensure reproducibility of the experiments, the main parameters of the simulation environment are explicitly defined. These include the number of interceptors and targets, environment dimensions, discretization time step, capture radius, speed and acceleration limits, sensing radius, and the safe inter-agent distance used in the definition of the collision metric. The complete set of parameters is summarized in Table 1.

Table 1

Main simulation parameters used in the experimental setup

Parameter	Value	Description
W (m)	10000	Width of the simulation environment
H (m)	10000	Height of the simulation environment
$N_{interceptors}$	3	Number of interceptors
$N_{targets}$	1	Number of targets
Δt (s)	0.1	Simulation time step
T (s)	350	Simulation time horizon
R_c (m)	5	Capture radius
$v_{interceptor,max}$ (m/s)	70	Interceptor maximum speed
$a_{interceptor,max}$ (m/s^2)	6	Interceptor maximum acceleration
$v_{target,max}$ (m/s)	55	Target maximum speed
$a_{target,max}$ (m/s^2)	2	Target maximum acceleration
d_{safe} (m)	2	Minimum allowed distance between interceptors
R_{sense} (m)	5000	Target sensing radius

6.1. Objective function and parameter optimization

Parameter optimization of decentralized interception algorithms is formulated as a multi-objective minimization problem that simultaneously accounts for interception efficiency, motion safety, and swarm coherence. To enable practical optimization within a unified framework, the multiple performance criteria are aggregated into a single oriented objective function using a weighted-sum approach.

The objective function is defined as

$$J = w_1 \cdot T + w_2 \cdot D_{total} + w_3 \cdot N_{coll} - w_4 \cdot \bar{\Phi}, \tag{4}$$

where T denotes the average mission completion time, D_{total} is the average cumulative trajectory length of the interceptors, N_{coll} represents the number of violations of the minimum safe inter-agent distance, $\bar{\Phi}$ is the mean swarm polarization over the simulation horizon, and w_i are non-negative weighting coefficients that define the relative priority of the individual criteria.

The formulation of the objective function reflects the inherent trade-offs of decentralized swarm interception. Minimization of T and D_{total} promotes fast and energy-efficient interception, while penalization of N_{coll} enforces motion safety in dense swarm configurations. The polarization term $\bar{\Phi}$ is included with a negative sign to favor coherent and coordinated swarm motion. By adjusting the weighting coefficients w_i, different operational priorities can be emphasized without modifying the underlying control laws.

The use of a scalarized objective function allows the application of gradient-based and stochastic optimization methods for parameter tuning. Importantly, the optimization is performed exclusively over the parameters of decentralized control laws and does not introduce centralized coordination or additional communication channels between agents. As a result, the decentralized nature of the interception algorithms is fully preserved while their performance characteristics are systematically improved.

7. Results

This section presents the results of the comparative evaluation of decentralized interception algorithms before and after parameter optimization. Quantitative values of all performance metrics are reported in Tables 2–5, where each table corresponds to a specific algorithm. The discussion below focuses on qualitative trends, relative improvements, and structural differences between the evaluated approaches.

7.1. Leader–follower pursuit

The results for the Leader–follower pursuit algorithm are summarized in Table 2. Parameter optimization leads to a pronounced improvement in all considered aspects of swarm behavior. The optimized configuration demonstrates increased swarm coherence and enhanced safety, reflected by larger inter-agent separation and a reduced number of safety violations. At the same time, interception efficiency improves substantially, as evidenced by faster mission completion and lower motion effort per drone. These observations indicate that the baseline performance of the leader–follower strategy is strongly constrained by heuristic parameter selection and that systematic optimization is essential for unlocking its full potential in decentralized interception scenarios.

Table 2
Performance metrics for the Leader–follower pursuit algorithm

Metrics	Basic	Optimized
$\bar{\Phi}$	0.99795	1.00000
d_{min} (m)	6.28311	8.04155
N_{coll}	137.3	83.6
Time (s)	203.1	137.89
Distance per drone (m)	13 723	8 978

7.2. Proportional Navigation

The performance metrics for the proportional navigation approach are reported in Table 3. In contrast to other algorithms, parameter optimization yields limited or adverse effects. While a slight increase in swarm coherence is observed, safety-related performance deteriorates, indicating a higher frequency of unsafe inter-agent interactions. Interception efficiency remains largely unchanged. This behavior highlights a fundamental limitation of proportional navigation when applied to decentralized swarm interception: aggressive tuning of pursuit parameters amplifies conflicts between independently acting agents due to the absence of explicit interaction and coordination mechanisms.

Table 3

Performance metrics for the Proportional Navigation algorithm

Metrics	Basic	Optimized
$\bar{\Phi}$	0.99561	0.99629
d_{min} (m)	68.9598	26.2821
N_{coll}	124.7	242.8
Time (s)	243.429	243.429
Distance per drone (m)	18 088	18 032

7.3. Local Interaction–Based Swarm Control (SLI)

The results for the local interaction–based swarm control algorithm are presented in Table 4. This approach exhibits the most balanced and robust improvement after parameter optimization. High swarm coherence is preserved, while safety is significantly enhanced, leading to the complete elimination of collision events. Simultaneously, interception efficiency improves through reduced mission duration and lower cumulative travel distance. These results confirm that decentralized algorithms explicitly incorporating local interaction terms are particularly well suited for systematic parameter optimization under limited communication conditions.

Table 4

Performance metrics for the Local Interaction–Based Swarm Control algorithm

Metrics	Basic	Optimized
$\bar{\Phi}$	0.99996	0.99998
d_{min} (m)	10.3714	19.3299
N_{coll}	27.6	0
Time (s)	186.575	137.39
Distance per drone (m)	13 054	8 939

7.4. Artificial Potential Field

The performance of the artificial potential field approach before and after optimization is shown in Table 5. Parameter tuning results in moderate but consistent improvements across all evaluation criteria. Swarm coherence remains high, safety metrics improve to a limited extent, and interception efficiency benefits from reduced time and motion costs. However, residual safety violations persist, indicating that inherent limitations of potential field–based control, such as local congestion and field interference effects, cannot be fully eliminated through parameter optimization alone.

Table 5

Performance metrics for the Artificial Potential Field algorithm

Metrics	Basic	Optimized
$\bar{\Phi}$	0.99999	1.00000
d_{min} (m)	8.05213	8.44684
N_{coll}	55.1	43.6
Time (s)	143.61	133.61
Distance per drone (m)	9 131	8 509

8. Conclusions

This paper addressed the problem of decentralized interception of moving aerial targets by a swarm of unmanned aerial vehicles operating under limited communication conditions. The interception task was formulated as a decentralized control problem in which each UAV independently generates motion control commands based on its own state and locally available observations, without centralized coordination or reliable inter-agent communication.

A set of representative decentralized swarm interception algorithms was analyzed within a unified simulation framework, including leader–follower pursuit, proportional navigation, artificial potential fields, and local interaction–based swarm control. To ensure a fair and reproducible comparison, all algorithms were evaluated under identical environmental conditions using a common set of formally defined performance metrics capturing interception efficiency, swarm coherence, and inter-agent safety.

A key contribution of this work is the formulation of parameter tuning as a scalarized multi-objective optimization problem. By aggregating multiple performance criteria into an oriented objective function, systematic parameter optimization was enabled without altering the decentralized nature of the control algorithms or introducing additional communication mechanisms. This approach addresses a common limitation of existing studies, where control parameters are often selected heuristically and without explicit justification.

The obtained results demonstrate that parameter optimization can significantly improve the performance of decentralized swarm interception algorithms; however, the magnitude and nature of the improvement strongly depend on the structural properties of the underlying control law. Algorithms explicitly incorporating local inter-agent interaction mechanisms exhibit the most favorable balance between interception efficiency, safety, and swarm coherence. In contrast, guidance laws originally developed for single-agent interception show limited suitability for dense decentralized swarm scenarios and may experience degraded safety performance after aggressive parameter tuning.

Overall, the presented framework provides a systematic and reproducible methodology for evaluating and improving decentralized swarm interception algorithms under communication-constrained conditions. The results highlight the importance of jointly considering efficiency, safety, and coherence when designing and tuning decentralized swarm control strategies and confirm that careful parameter optimization is essential for their practical deployment.

Future research directions include extending the framework to heterogeneous swarms, incorporating dynamic or intermittent communication constraints, and investigating adaptive or online parameter optimization methods for scenarios with non-stationary target behavior.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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