Optimization of Autonomous Agents Group Movement Based on Artificial Intelligence Elements*

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Abstract

This study focuses on optimizing the group motion of autonomous mobile robotic systems (MRS) moving in formation within a relative coordinate system without relying on global positioning. New optimization problem formulations are proposed for a hybrid swarm motion algorithm based on local data, including pairwise distances and angles, as well as conformal transformations, in both group and swarm settings. A set of evaluation criteria was developed, including cohesion, formation stability, energy efficiency, and the number of collisions. Simulation results involving 1,000 agents demonstrate the effectiveness of the hybrid optimization algorithm, achieving a task success rate of 94% with no collisions. Experiments involving four drones confirmed consistency with the simulation results.

Keywords

optimization, local navigation, groups of autonomous robots, swarm intelligence, relative coordinates, autonomous agents, conformal transformation group

1. Introduction

The use of groups of mobile robotic systems (MRS) for autonomous task execution, including transportation, monitoring, and irrigation, is rapidly increasing [1]. Global positioning systems are often unavailable or inaccurate in indoor environments, urbanized areas, and mountainous terrain. This necessitates the development of leaderless local navigation algorithms based on pairwise distances and angles [2].

The objective of this work is to develop optimization models for controlling an MRS group as a single entity while accounting for obstacles and hardware constraints, formalize the corresponding problem statements, and design an algorithm that ensures collision avoidance.

2. Related Work

A review of the literature [1, 3–5] demonstrates the advantages of swarm algorithms, including Vicsek, Boids, Particle Swarm Optimization (PSO), and the Potential Field Method (PFM). However, these approaches lack adaptations to relative coordinate systems.

Based on the authors' previous studies [2, 6], a hybrid algorithm was developed to balance motion characteristics while ensuring collision avoidance. Nevertheless, extensive testing revealed difficulties in maintaining a stable formation. These difficulties were caused by errors that led to formation deformation and excessive corrective motion by the MRS. Therefore, optimizing the motion of individual elements within an MRS group during autonomous task execution may address these issues and improve overall efficiency.

A detailed description of the advantages and disadvantages of the Vicsek, Boids, PSO, and PFM algorithms, as well as the developed algorithm and the results of their comparative evaluation, is presented in [2, 6].

*ITS-2025: Information Technologies and Security, December 11, 2025, Kyiv, Ukraine

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CEUR Workshop Proceedings ceur-ws.org ISSN 1613-0073

published 2026-11-26

CEUR-WS.org/Vol-4337/paper23.pdf

3. Methodology

The study is based on simulations conducted in Python using the Google Colab environment and involving 1,000 MRS. The algorithms use local data, including pairwise distances d_{ij}, angles θ_{ij}, relative spatial orientation, and altitude. The simulation results were validated through practical experiments involving four drones.

Optimization problem formulations were developed for the following algorithms:

- **Vicsek**, which minimizes deviations in direction from the average direction of the local neighborhood while accounting for angular information [4].
- **Boids**, based on minimizing dispersion relative to the local center of mass.
- **PFM**, which minimizes total potential energy [3].
- **PSO**, which balances individual and collective experience [5].

The following evaluation criteria were used: average and maximum inter-agent distances, deviation from the target position, number of collisions, velocity, formation stability, and energy efficiency. The algorithms were compared in terms of centralized and decentralized control, as well as their applicability to formation and amorphous motion.

A proprietary hybrid algorithm, combining PSO and PFM with local interactions, was developed. Unlike the algorithms considered above, the proposed approach provides formal safety guarantees through proactive collision prevention, making it particularly suitable for tasks involving large numbers of MRS.

4. Results

Having established the objective and relevance of the study, we now consider the data available within the proposed problem formulation. The individual elements of the group are referred to as agents. Depending on their assigned roles, agents may be classified as leaders or followers.

The relative positioning problem for an MRS group is based on the following initial set of known parameters:

1. **Metric data**. For each ordered pair of agents in the group, the Euclidean distance between the agents in three-dimensional space is known.
2. **Angular observations**. For each pair of agents, the bearing, represented as a direction vector, is measured in the observer's local coordinate system, thereby defining their relative angular positions.
3. **Relative spatial orientation**. For each pair of agents, qualitative information about their mutual position within the surrounding space is available. This information includes the signs of the projections of the relative displacement vector onto the axes of the local coordinate system, such as left/right and front/back. It enables the reconstruction of oriented relationships between agents and eliminates mirror ambiguities in geometric reconstruction.
4. **Absolute orientation and altitude**. Each agent has access to measurements of the Earth's magnetic field vector, enabling the determination of magnetic north and the orientation of its local coordinate system relative to the cardinal directions. Each agent also continuously estimates its altitude relative to a reference surface, such as the geoid, using barometric sensors, radar altimeters, or other appropriate sensors.
5. **Global coordinates with limited accuracy**. Each agent estimates its global coordinates using inertial measurement units, optical-flow-based odometry, or sensor fusion. These estimates have limited accuracy because of cumulative errors that increase over time and with the distance traveled. The error may be corrected when access to a global coordinate system becomes available through satellite positioning systems, ground-based navigation sources, or episodic airborne mesh networks with appropriate capabilities.

4.1. Sources of Errors and Deformation of MRS Group Topology in Competitive Robotics

1. **Communication delays**. Command transmission through an intermittent relay network introduces a variable time delay, $\tau(t)$, causing followers to receive and execute commands with a latency relative to the leader.
2. **Platform heterogeneity and calibration**. Although the agents belong to the same technical class, they are not perfectly identical. Differences in dynamic characteristics, sensor accuracy, and controller parameters arise from manufacturing tolerances and varying degrees of wear. In addition, the calibration of each agent's sensing and actuation systems introduces individual errors.
3. **Resulting deformation**. The combined effects of communication delays, differences in response dynamics, and individual execution errors result in systematic and stochastic deviations of each follower's actual relative position from its prescribed position in the ideal formation. Consequently, the formation undergoes continuous, undesirable deformations that may accumulate during maneuvering.

The execution of MRS tasks often requires prolonged group motion while maintaining a prescribed formation. Therefore, in addition to established group-motion models and collision-avoidance algorithms, topological methods based on conformal transformations can be used to address problems caused by formation deformation. These methods are considered in greater detail below.

4.2. Conformal Transformations as a Mathematical Foundation for Group Geometry Control in Adaptive Swarms

Previous studies [2, 6] have shown that a fundamental problem in the collective control of robot groups, including swarms and cooperative systems, particularly UAV groups, is distinguishing desired collective maneuvers, such as turning, convergence, or formation scaling, from undesirable deformations caused by errors, communication delays, and agent heterogeneity. To address this problem, the mathematical framework of conformal transformations is considered.

A conformal transformation [7-15] is a mapping that preserves angles between curves at each point. In two- and three-dimensional spaces, this implies the preservation of local geometric shape up to a scale factor. Conformal transformations in Euclidean space can generally be represented through combinations of several basic operations, including translation, rotation, uniform scaling, and, in the most general case, inversion. For MRS formation control, the relevant subset usually consists of translation, rotation, and uniform scaling.

4.3. Geometric Interpretation and Significance for Agent Groups

If an ideal robot formation is represented as a configuration of points in space, a uniform similarity transformation of this configuration preserves its angular relationships and relative proportions. This makes conformality a useful concept for analyzing swarm states [7-14]:

1. **Permissible changes**. Leader motion, collective rotation caused by environmental disturbances such as wind, or smooth convergence of agents to pass through a narrow passage can be described by translation, rotation, and uniform scaling.
2. **Undesirable deformations**. Stretching, twisting, or flattening of a formation caused by communication delays or differences in agent dynamics represent deviations from conformality. Such local distortions cannot be described by a single global translation, rotation, and uniform scaling.

Thus, the key idea is to reformulate the problem from strict tracking of ideal coordinates to the optimization of conformity with an ideal formation. Under conditions of noise and communication

delays, an MRS group or swarm should not attempt to maintain an unattainable exact configuration. Instead, it should seek a state in which the actual configuration is as close as possible to a permissible conformal transformation of the ideal configuration.

In other words, the objective is to determine the global parameters – the translation vector **T**, rotation matrix **R**, and scaling factor s – that best map the ideal relative positions of the agents to their observed actual positions. The residual deviation η, representing the non-conformal component of the deformation, is then minimized and used as a measure of formation quality.

4.4. Mathematical Representation

For agent i with ideal relative position P_i in the formation coordinate system, the actual position can be represented as:

$$P_i^{target} = s \cdot R \cdot P_i + T + P^{leader} + \eta, \quad (1)$$

where (s, R, T) are the corresponding terms represent the estimated global transformation parameters for the entire group, and the residual term **η** represents the non-conformal deformation.

The task of each agent is to adjust its trajectory to minimize its deviation from the corresponding target position while simultaneously maintaining local conformity with its neighbors.

This approach is consistent with both the leader-follower hierarchy and the principles of swarm intelligence and cooperative robotics:

1. **Leader**. The designated leader, or alternatively the group center of mass, may estimate the global transformation parameters (s, R, T) that define the collective maneuver.
2. **Followers**. Each follower locally optimizes its position using information obtained from neighboring agents and attempts to preserve conformity within its local neighborhood.
3. **Swarm resilience**. Even if communication with the leader is lost, local conformity-preserving rules can help prevent the formation from collapsing.

Consequently, conformal transformations can provide an effective mathematical framework for the development of resilient, adaptive, and geometrically stable swarms. Such an approach enables the group to perform maneuvers under real-world conditions while minimizing the distortions that compromise the functionality of the formation.

This framework also allows a transition from attempting to eliminate all deviations to controlling an equivalence class of admissible configurations. Such a transition is important for achieving efficient operation in dynamic and uncertain environments.

4.5. Problem Statement for Formation Correction

It is necessary to synthesize a distributed algorithm for correcting the relative positioning of agents. The algorithm should compensate for the aforementioned deformations in real time while maintaining the integrity and geometric properties of the group formation with acceptable accuracy. The constraints imposed by a dynamic communication network and agent heterogeneity must also be taken into account.

4.6. Optimization of Conformal Deformations

The optimization of conformal deformations in a group of agents is a promising approach to this problem. It enables undesirable deformations to be distinguished from admissible transformations while preserving the overall geometric structure of the formation.

The core idea is that, instead of performing an exact reconstruction of the ideal configuration, which may be computationally and energetically inefficient, the algorithm optimizes the formation so that its actual configuration approaches the ideal one as closely as possible within the class of

admissible transformations, including translation, rotation, and uniform scaling. At the same time, non-conformal distortions, such as relative shifts and local shape deformations of individual formation elements, are minimized.

5. Overview of Possible Optimization Criteria

The criteria used to determine whether optimization improves the relative positioning and reduces formation deformation within an MRS group or swarm can be divided into two categories: global criteria, which characterize the formation as a whole and may be computed centrally or collectively, and local criteria, which can be evaluated by individual agents using information received from their neighbors.

5.1. Global Criteria at the Formation Level

5.1.1. Objective function for minimizing the mean squared deviation from the conformal model

For the current positions of the agents, the optimal transformation parameters are determined to map the ideal relative positions $\boldsymbol{P}^{id}$ to the observed positions $\boldsymbol{P}$. The parameters $\{s, \boldsymbol{R}, \boldsymbol{T}\}$ are optimized to minimize the total error:

$$E_{global} = min_{s,R,T} \sum_i \left\| P_i - \left(s \cdot R \cdot P_i^{id} + T \right) \right\|^2. \quad (2)$$

5.1.2. Constraint on the preservation of relative angles (conformality)

This criterion penalizes violations of conformality, such as changes in the angles between vectors defining the formation. It can be expressed as the minimization of the differences between the cosines of corresponding angles in the current and ideal configurations.

5.1.3. Uniform scaling condition

This condition requires the local scaling factors in different parts of the formation to remain as close as possible to a single global value. This prevents undesirable local compression or stretching of individual regions.

5.2. Local Criteria at the Agent and Network-Edge Levels

These criteria are particularly important for distributed optimization under intermittent communication conditions.

Minimization of local segment deformation. For each pair of neighboring MRS, (i, j), a function of the following form is minimized:

$$E_{ij}^{local} = \alpha \cdot \left(\left\| P_i - P_j \right\| - s \cdot d_{ij} \right)^2 + \beta \cdot \left\| \Xi_{ij} - R \cdot \Xi_{ij}^{id} \right\|^2, \quad (3)$$

where d_{ij} is the ideal distance between agents i and j, the corresponding orientation term represents the current orientation of the segment (i, j), and the ideal orientation term represents its desired orientation. The coefficients α and β are weighting factors. This criterion is particularly important because it can be evaluated locally using information obtained from neighboring agents.

Alternatively, in vector form:

$$E_{ij}^{local} = \alpha \left(\left\| P_i - P_j \right\| - s \cdot d_{ij} \right)^2 + \beta \left\| \frac{P_i - P_j}{\left\| P_i - P_j \right\|} - R \frac{P_i^{id} - P_j^{id}}{\left\| P_i^{id} - P_j^{id} \right\|} \right\|^2. \quad (4)$$

5.3. Preservation of relative positions in the local coordinate system

Each agent seeks to preserve the relative angles and proportions defined by its immediate neighbors, thereby maintaining local conformality within the formation.

5.4. Smoothing and regularization criterion

A penalty is introduced for significant differences in the estimated conformal transformation parameters, such as s and $\mathbf{R}$, between neighboring agents. This prevents the formation of sharp discontinuities or "seams" in the deformed configuration and promotes the propagation of consistent estimates throughout the network.

Thus, the optimization of conformal deformation provides an architecturally appropriate approach to controlling the motion of an MRS group with the characteristics described above. It naturally accounts for key constraints, including communication delays and platform heterogeneity, and supports the development of a robust distributed formation-maintenance algorithm. Rather than attempting to eliminate all deviations, the algorithm specifically corrects undesirable geometric distortions.

Taking the above optimization criteria into account, we now formulate the optimization problem for an MRS group.

6. General Formulation of the Optimization Problem for an MRS Group

In real time, the algorithm continuously solves, or iteratively updates, the following optimization problem.

Minimize:

$$J^{total} = \lambda_1 \cdot E^{global} + \lambda_2 \cdot \sum E_{ij}^{local} + \lambda_3 \cdot \langle regularization_criterion \rangle . \quad (5)$$

Subject to:

1. Physical constraints of the MRS, including maximum velocity and acceleration.
2. Safety constraints, including the minimum allowable distance between agents.
3. Communication-topology constraints, such that optimization is performed only over communication links available at the current time.

An **integrated cost function** is used to combine the relevant criteria into a single optimization problem. The task of each agent is therefore formulated as a local optimization problem that simultaneously incorporates all applicable objectives and constraints.

Consensus provides the mechanism through which the agents collectively achieve the stated objective. For agent i, the motion parameters are determined by minimizing:

$$J_i = \sum_{j \in N(i)} \left[w^{dist} \cdot E_{ij}^{dist} + w^{cons} \cdot \left(s_i - s_j \right)^2 \right] + w^{angle} \cdot E_i^{angle} + w^{track} \cdot \left\| P_i - P_i^{ref} \right\|^2 . \quad (6)$$

where J_i is the local objective function. Through terms such as $(s_i - s_j)^2$ in the cost function, the minimization of its local objective function causes agent i to:

1. Adjust its position P_i to satisfy local distance and angular constraints, such as E_{ij}^{dist} and E_i^{angle}.
2. Adjust its estimates of the global transformation variables, such as s_i and $\boldsymbol{R}_i$, so that they converge toward the corresponding estimates of neighboring agents.

Thus, the local optimization process performed by each agent simultaneously constitutes a step in a distributed consensus algorithm. This principle is fundamental to distributed optimization methods and Distributed Model Predictive Control (DMPC).

7. Hybrid Algorithm for MRS Agents

7.1. Initialization

The leader disseminates the parameters of the target formation, including the ideal configuration $\boldsymbol{P}^d$, the desired velocity v^{des}, and the desired orientation ψ^{des}.

7.2. Operation at Each Control Cycle

For each follower MRS, the following steps are performed during every control cycle.

7.2.1. Step 1: State estimation

Agent i receives, or estimates, the positions $\boldsymbol{P}_j$ and parameter estimates s_j and ψ_j of its immediate neighbors $j \in \mathcal{N}(i)$ through the available intermittent communication network.

7.2.2. Step 2: Local optimization with consensus elements

Agent i solves its local minimization problem:

$$J_i = \sum_{j \in \mathcal{N}(i)} \left[k_1 \cdot \left(\left\| P_i - P_j \right\| - d_{ij} \right)^2 + k_2 \cdot \left(\psi_i - \psi_j \right)^2 + k_3 \cdot \left(s_i - s_j \right)^2 \right] + k_4 \cdot \left\| v_i - v^{des} \right\|^2. \quad (7)$$

where the term $(\psi_i - \psi_j)$ promotes consensus on orientation, while $(s_i - s_j)$ promotes consensus on the scaling factor.

7.2.3. Step 3: Execution

Agent i applies the calculated control command u_i to adjust and correct its trajectory.

7.3. Role of the Leader

The leader's updated objectives $v^{des(new)}$ i $\psi^{des(new)}$ are gradually propagated through the network via the consensus terms in Equation (7), even when not all agents receive the command simultaneously.

8. Application of Swarm Intelligence Principles to Drone Formation Control

Swarm-based approaches fundamentally change the control paradigm. Instead of relying on centralized planning or a rigid hierarchy, collective behavior emerges through simple local interaction rules. This approach is well suited to the conditions defined in the problem statement, including intermittent communication, agent heterogeneity, and environmental uncertainty [1-6]. The key principles of swarm operation are decentralization, self-organization, emergent behavior, robustness, and fault tolerance. Their application in the present context is considered below.

8.1. Decentralization

The core principle of swarm control is the absence of a single leader or central control node; decisions are instead made collectively through local interactions.

In a swarm, a designated leader, if present, is no longer the sole source of control commands. Such an agent may act as a reference agent or provide the general direction of motion, while the formation itself is maintained autonomously through local interactions. Even in the event of complete loss of communication with the leader, the swarm can continue moving in the last known direction or switch to a stabilization mode.

8.2. Self-Organization Through Simple Rules

The self-organization rules (separation and collision avoidance, velocity consensus, cohesion) applied by each agent are independent of centralized control and rely exclusively on information obtained from neighboring agents. These rules are formalized below in terms of potential functions (Equations 8-12).

8.3. Emergent Behavior

Complex collective behaviors, such as V-shaped flight, formation changes, and obstacle avoidance, emerge from the interaction of these simple local rules rather than being explicitly prescribed by an operator or rigidly encoded in the motion-control algorithm.

This principle directly addresses the formation-deformation problem. The swarm continuously adapts to changing conditions, disturbances, and local errors while seeking to maintain a stable collective configuration.

8.4. Robustness and Fault Tolerance

Swarm architecture assumes that the loss or failure of an individual agent does not necessarily compromise the operation of the swarm as a whole. If a drone fails or communication with it is lost, neighboring agents can automatically redistribute their interaction forces and adjust their relative positions. As a result, the formation can smoothly reconfigure while maintaining its overall functionality.

Based on these principles, a swarm model for maintaining a stable formation in the presence of conformal deformations is considered below.

9. Swarm Model for the Conformal Deformation Problem

At each control cycle, agent i computes the resultant control input as a weighted sum of potential-based components:

$$u_i = w_1 \cdot \nabla \Phi^{repulsive} + w_2 \cdot \nabla \Phi^{velocity\ consensus} + w_3 \cdot \nabla \Phi^{conformal}. \quad (8)$$

The components of the resulting control input, represented as the sum of the corresponding potentials or their gradients, are as follows.

9.1. Repulsive Potential for Collision Avoidance

$$\Phi^{repulsive} = \sum_{j:d_{ij}<d^{safe}} \left(d^{safe} - d_{ij}\right)^2. \quad (9)$$

This component ensures that the distance between neighboring agents remains above the minimum allowable safety threshold.

9.2. Velocity-Consensus Potential for Maneuver Synchronization

$$\Phi^{velocity\ consensus} = \sum_{j \in N(i)} \left\| v_i - v_j \right\|^2. \quad (10)$$

This component promotes velocity alignment among neighboring agents and thereby synchronizes collective maneuvers.

9.3. Conformal Formation Potential Combining Swarm Principles with Conformal Deformation Optimization

$$\Phi^{conformal} = \sum_{j \in N(i)} \left[\lambda_{dist} \cdot \left(d_{ij}^{curr} / L_i - d_{ij}^{id} \right)^2 + \lambda_{angle} \cdot \left(\cos\left(\theta^{curr}\right) - \cos\left(\theta^{id}\right) \right)^2 \right] \quad (11)$$

The relative distances d_{ij}^{curr} are normalized using agent i's local estimate of the formation scale, L_i. Agent i estimates L_i based on observations of its neighbors and seeks to achieve consensus with their corresponding estimates through an additional rule:

$$L_i(k+1) = L_i(k) + \mu \cdot \Sigma\left(L_j(k) - L_i(k)\right). \quad (12)$$

Thus, in the swarm-based approach, the formation scale is determined not by a direct command from a leader but through collective agreement among agents regarding the current scale L.

10.Swarm Agent Structure

To explain the operation of the proposed swarm-control algorithm based on the optimization of group topology, consider the structural diagram of a swarm agent shown in Fig. 1. The agent architecture supporting swarm operation consists of the following functional blocks.

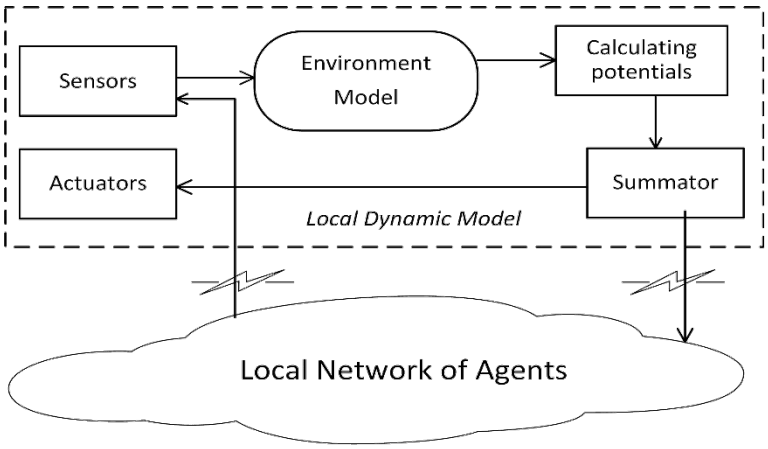


Figure 1: Structural diagram of a swarm agent.

10.1. Environment Model

Each agent maintains a model of its immediate neighborhood, typically including the 3-5 nearest neighboring agents. The model is constructed using sensor data, such as inter-agent distances and bearings, together with limited information received through the communication network, including positions, velocities, and scale estimates L_j.

10.2. Potential Computation

The gradients of all potential functions are computed in parallel using the current local model of the environment.

10.3. Local Dynamic Model

The local dynamic model enables each agent to predict the effect of its control command $\mathbf{u}_i$ and enforce physical constraints, such as maximum acceleration. It may be implemented as a simplified predictor of the agent's motion.

10.4. Summation Block

The summation block generates the agent's final motion command by combining the outputs of the individual control components. The weights w_1, w_2, and w_3 may be adjusted adaptively. For example, w_1 may increase rapidly when a risk of collision is detected.

We now consider the specific problems encountered during long-term testing of group and swarm motion and the methods used to address them.

11.Methods for Addressing Specific Motion Problems in Agent Groups

Network delays, platform heterogeneity, and intermittent connectivity are naturally accommodated within the potential-based control structure: each agent acts on the most recently available data

from its neighbors, employs its own dynamic model, temporarily excludes unavailable neighbors from the interaction function, while the potential $\Phi^{conformal}$ continuously adjusts the formation geometry according to the estimates of scale L_i and velocity v_i.

12.Role of the Leader in a Swarm

In a swarm architecture, the leader serves primarily as a means of influencing the swarm rather than as its centralized controller. Through the leader, the operator may [2, 6]:

1. **Influence the target field**. The operator may specify an additional global attraction potential toward a particular point or along a desired trajectory. The leader can then serve as a reference for directing the swarm toward that point or along that trajectory.
2. **Set rule parameters**. Desired inter-agent distances, d_{ij}^{id}, or the target scale, L^{target}, may be modified through the leader, after which the updated parameters propagate through the swarm via consensus mechanisms.
3. **Act as a driving agent**. The leader may simply move along the required trajectory. The velocity-alignment rule causes neighboring agents to adapt to its motion, allowing the maneuver to propagate progressively throughout the swarm.

Thus, the swarm-based approach is suitable for problem settings characterized by dynamic communication networks and limited communication reliability. Rather than attempting to eliminate formation deformations through a single complex centralized optimization process, the swarm continuously seeks a state of minimal deformation through simple, local, and highly resilient interaction rules.

13.Aggregated Mathematical Model and Optimization Problem Formulation for a UAV Swarm

13.1. Aggregated Mathematical Model and Optimization Problem Formulation for a UAV Swarm

The swarm consists of a set of Nheterogeneous MRS with dynamics:

$$P_i = v_i. \tag{13}$$

$$v_i = u_i + \delta_i(t) + d_i(P_i, t), \tag{14}$$

where P_i,, v_i, and $u_i \in R^8$ denote the position, velocity, and control input, respectively; $\delta_i(t)$ is an execution error due to agent heterogeneity; and $\boldsymbol{d_i(\cdot)}$ represents external disturbances. At discrete instants t_k, each agent i accesses local measurements of neighbors j ∈ Ni(t) (distance, bearing, relative position), plus its own orientation and altitude h_i. Data exchange occurs over an intermittent network $G(t) = (V, E(t))$ with delay $\tau_{ij}(t) \in [\tau_{min}, \tau_{max}]$. Agent $i = 1$ may act as operator-controlled leader; remaining agents combine leader information with local self-organization.

As introduced above, the actual configuration deviates from the ideal one, $\boldsymbol{P_{id}}$, via a global similarity transform plus residual deformation:

$$P_i(t) \approx s(t) R(t) P_i^{id} + T(t) + \varepsilon_i(t), \tag{15}$$

with $s(t)$, $\boldsymbol{R(t)}$, $\boldsymbol{T(t)}$ the global scale, rotation, and translation, and $\boldsymbol{\varepsilon_i(t)}$ the non-conformal deformation to be minimized. Its sources are communication delays τ_{ij}, heterogeneity $\boldsymbol{\delta_i(t)}$, measurement noise, and topology constraints $G(t)$.

The total cost combines a global component, periodically solved by the leader,

$$J^{global}(t) = \min_{s,R,T} \sum_{i=1}^{N} \square \| P_i(t-\tau_i) - (s \cdot R \cdot P_i^{id} + T) \|^2, \tag{16}$$

with a local component optimized in real time by each agent over a receding horizon $\boldsymbol{T_h}$:

$$J_i(P_i, u_i) = \int_t^{t+T_h} [\Phi_{local}(P_i(\tau)) + /\!/ u_i(\tau) /\!/_R^2] d\tau + V_{terminal}(P_i(t+T_h)), \quad (17)$$

where Φ_{local} sums four terms already defined in the group-level formulation above (conformal attraction, safety repulsion, velocity/scale alignment, and leader-following), reused here with the leader's optimal s^*, $\boldsymbol{R}^*$, $\boldsymbol{T}^*$:

$$\Phi_i^{conf} = \sum_{j \in N_i(t)} w_{ij} \cdot \left[\alpha \cdot \left(\left\| P_i - P_j \right\| - s^* \cdot d_{ij}^{id} \right)^2 + \beta \cdot \left(\angle(P_i, P_j, P_k) - \theta_{ijk}^{id} \right)^2 \right], \quad (18)$$

Safety potential (repulsion and separation) increases continuously as the distance between neighboring agents approaches the minimum safety threshold R_{rep}:

$$\Phi_i^{rep} = \sum_{j:\|P_i - P_j\| < R_{rep}} \gamma \cdot \exp\left(\frac{-\left\| P_i - P_j \right\|}{\left(R_{rep} - \left\| P_i - P_j \right\| \right)} \right), \quad (19)$$

Velocity alignment potential (alignment and consensus):

$$\Phi_i^{align} = \sum_{j \in N_i(t)} \mu \cdot \left\| v_i - v_j \right\|^2 + \upsilon \cdot \left(L_i - L_j \right)^2, \quad (20)$$

where L_i denotes the agent's local estimate of the formation scale or another relevant collective parameter. This term implements a distributed consensus mechanism.

Leader-following potential promotes motion toward the globally optimal target position

$$\Phi_i^{goal} = \left\| P_i - \left(s^* \cdot R^* \cdot P_i^{id} + T^* \right) \right\|, \quad (21)$$

The weights α, β, γ, μ, and υ may be adjusted adaptively depending on communication quality and the degree of confidence in the information received from neighboring agents.

We now consider the formulation of the real-time optimization problem, which differs for the leader and the remaining swarm agents.

13.2. Real-Time Distributed Optimization Problem

At each control step, each non-leader agent i must determine a control trajectory $u_i(\cdot)$ over a prediction horizon T_h that minimizes the local swarm objective function $J_i(P_i, u_i)$.

The optimization is subject to the following constraints.

1. Dynamic constraints $\dot{P}_i = v_i$, $v'_i = u_i$ subject to the control-input bound $\|u_i\| \le u_{max}$.
2. Safety constraints $\|P_i(t) - P_j(t)\| \ge d_{min}$, $\forall_j$ for all relevant neighboring agents j.
3. Communication constraints. Information is available only from agents $j \in N_i(t)$, as determined by the current intermittent communication network.
4. Information-delay constraints. The available state information of neighboring agents, including P_j and v_j, may be delayed by $\tau_{ij}(t)$.
5. Target-parameter constraints. The transformation parameters received from the leader, including s^*, $\mathbf{R}^*$, and $\mathbf{T}^*$, may be subject to a communication delay τ_{io}.

For the leader, the optimization problem additionally includes a global optimization procedure for determining the optimal transformation parameters s^*, $\mathbf{R}^*$, and $\mathbf{T}^*$, as well as the generation of a reference trajectory for the swarm.

13.3. Desired Properties of the Solution and Success Criteria

The optimal control input u_i(t) should satisfy the following requirements.

13.3.1. Asymptotic stability of the formation

$$\lim_{t \to \infty} \varepsilon_i(t) = 0, \left\| \varepsilon_i(t) \right\| = \varepsilon_{max} \quad (22)$$

This condition requires the formation to converge toward the desired configuration over time.

13.3.2. Robustness

The swarm should preserve its connectivity and maintain an acceptable formation geometry under the following conditions:

- loss or failure of individual agents;
- temporary communication outages, including cases in which $N_i(t) = \emptyset$;
- bounded execution errors $\boldsymbol{\delta}_i(t)$ and external disturbances $d_i(t)$.

13.3.3. Adaptability to dynamic communication topology

The criteria Φ_i^{conf} and Φ_i^{align} are automatically recalculated whenever the local neighborhood or communication graph $N_i(t)$ changes.

13.3.4. Preservation of conformality

The magnitude of the non-conformal deformation $\varepsilon_i(t)$ should be minimized, including during collective maneuvers involving changes in the optimal scale s^* or rotation $\boldsymbol{R}^*$. Solving this optimization problem requires an architectural decomposition into three levels.

14.Proposed Architecture for Solving the Optimization Problem

The proposed approach employs a hierarchical architecture consisting of the following levels:

1. **Upper level (leader)**. Periodic global estimation of the conformal transformation parameters, s^*, $\mathbf{R}^*$, and $\mathbf{T}^*$, using the least-squares method.
2. **Middle level (all agents)**. A distributed Kalman consensus algorithm for estimating the states of neighboring agents while accounting for communication delays.
3. **Lower level (all agents)**. Distributed Model Predictive Control (DMPC), which minimizes the local objective function J_i over a prediction horizon T_h. Each agent solves its own optimization problem while exchanging only predicted trajectories with its immediate neighbors.
4. **Adaptive mechanism**. The weights in the local potential function, Φ^{local}, are adjusted according to communication quality indicators, such as packet loss rate and communication delay magnitude τ_{ij}.

The dynamics of each agent are described by a double-integrator model $P_j = v_i$, $v_i = u_i$, where $\boldsymbol{P}_j \in R^2$ denotes the agent's position, $\mathbf{v}_i \in R^2$ denotes its velocity, and $\mathbf{u}_i \in R^2$ denotes the control input.

For each agent i, a set of local neighbors is defined as:

$$N_{i\square} = \{ j \neq i \,/\, /\!/ P_j - P_i /\!/ \leq R \}. \tag{22}$$

The control law is defined as:

$$u_i = \sum_{j \in N_i} u_{ij}^{spring} + \sum_{j \in N_i} u_{ij}^{rep} - k_d v_i. \tag{23}$$

where $k_d > 0$ is the damping coefficient. The control law includes an elastic component:

$$u_{ij}^{spring} = k_s (P_j - P_i /\!/ - d_{ij}^{des}) \frac{P_j - P_i}{P_j - P_i /\!/}. \tag{24}$$

where $k_s > 0$ is the spring stiffness coefficient. And a short-range repulsive component:

$$u_{ij}^{rep} = \begin{cases} k_r (d_{min} - /\!/ P_j - P_i /\!/) \dfrac{P_j - P_i}{/\!/ P_j - P_i /\!/}, & /\!/ P_j - P_i /\!/ < d_{min}, \\ 0, \text{else}. \end{cases} \tag{25}$$

where $k_r > 0$ is the repulsion coefficient.

The control input is additionally subject to saturation:

$$u_i \leftarrow min\left(1, \frac{u_{max}}{\| u_i \|}\right) u_i. \quad (26)$$

This algorithm is fully distributed and local. It does not require global optimization or iterative procedures during operation.

15.Practical Study of the Developed Algorithm

The simulation results presented in Table 1. demonstrate the performance of the developed Elastic Formation algorithm based on conformal transformations in comparison with several well-known approaches for a formation consisting of eight agents.

Table 1
Comparison of group-motion algorithms for an eight-agent formation according to selected performance metrics

Method	RMS Deformation	Max Distance	Collisions	Energy
Potential Fields	3.987	7.475	222	145005
Vicsek	0.266	10.056	0	0
Boids	2.479	5.528	0	97.362
Elastic Formation	0.136	10.499	0	703.921

For a correct interpretation of the comparative simulation results, the employed metrics must first be clearly defined. Table 1 reports RMS formation deformation as the primary indicator of shape preservation [15].

A comparative analysis of the results highlights the characteristic properties of each approach. The Potential Field Method, despite maintaining relatively limited agent dispersion, exhibits substantial formation deformation and high energy consumption. This behavior is consistent with the known limitations of local potential-based methods when no explicit formation objective is included.

The Vicsek algorithm eliminates dangerous proximity events and exhibits near-zero energy consumption. However, it does not guarantee accurate maintenance of the prescribed formation geometry because its primary objective is directional alignment rather than preservation of a specific spatial configuration.

The Boids model demonstrates a compromise between these approaches. It provides stable swarm behavior without collisions and with moderate energy expenditure but does not effectively maintain a prescribed formation geometry, as reflected in its relatively high RMS deformation.

The Elastic Formation algorithm demonstrates the best performance in terms of formation maintenance. It achieves the lowest root-mean-square deviation from the desired configuration while completely avoiding dangerous proximity events. Although its energy consumption is higher than that of some of the other heuristic methods, it remains controlled and does not result in dynamic instability.

The results of the broader simulation study are summarized in Table 2. One of the key scientific challenges addressed in this work is multi-agent modeling of autonomous local navigation for groups and large swarms of mobile robotic systems. Practical experiments involving four mobile robotic systems demonstrated an 85% correspondence with the simulation results [15].

Table 2
Simulation Results for Agent Motion in Environments with Static and Dynamic Obstacles

Parameter	Value	Unit
Agents	1000	arbitrary units
Simulation execution time	189,575	seconds
Safety metrics		
Collisions	0	incidents
Dangerous proximity events	0	incidents
Minimum distance	4.9	meters
Algorithm performance metrics		
Average step execution time	187.85	microseconds
Maximum step execution time	1931.49	microseconds
Solution success rate	94.3	percent
Navigation metrics		
Mean deviation	12.3	meters
Mean agent speed	45.7	meters per second

16.Conclusion

This work investigates a locally centered optimization model for autonomous mobile robotic systems that does not rely on global coordinates. Conformal transformations are proposed as a mathematical framework for optimizing the maintenance of group and swarm structures. Relevant optimization criteria are defined, and optimization problems are formulated for both group-based and swarm-based architectures, taking their respective characteristics into account.

A comprehensive approach to optimizing the conformal topology of a collective of autonomous agents is proposed. The use of conformal transformations makes it possible to distinguish desired collective maneuvers from undesirable deformations caused by communication delays, platform heterogeneity, and dynamic disturbances.

The developed hybrid algorithm combines elements of PSO and PFM and aims to achieve a balance among formation stability, motion efficiency, and safety. According to the simulation results, it provides inter-agent distances that are 45% shorter than those achieved by the Boids algorithm and demonstrates 20% better energy efficiency than Vicsek. The proposed hybrid motion-control architecture for groups and swarms combines elements of the leader–follower hierarchy, swarm intelligence, and distributed optimization. It incorporates both local criteria, including distance and angle preservation, and global criteria, including minimization of the mean squared error. This architecture is designed to maintain robust operation under intermittent communication failures and limited computational resources while ensuring collision-free motion.

Algorithmic and software tools for simulating the motion of UAV swarms of varying sizes under hybrid control systems were also developed. Computational experiments demonstrated collision-free motion in a dense formation consisting of a large number of agents. The results demonstrate the potential of the proposed approach as a multilevel optimization framework for safe group motion and collision avoidance in multi-agent systems operating in complex environments containing obstacles and other dynamic agents.

The proposed algorithm contributes to the development of adaptive swarms for operation in dynamic and adversarial environments, including applications such as reconnaissance and search-and-rescue operations.

Declaration on Generative AI

During the preparation of this work, the authors used Grok 4.1 Fast, ChatGPT-5.2, and Grammarly for grammar and spelling checks. After using these tools, the authors reviewed and edited the content as necessary and take full responsibility for the content of the publication.

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