The Group Movement Optimization of Autonomous Agents in a Locally-Centric Navigation Model*

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Abstract
The scope of autonomous robotic systems capable of performing tasks without global positioning is rapidly expanding. This study aims to develop algorithms for optimal control of autonomous agent groups in a relative coordinate system using local information (pairwise distances and angles) without relying on global positioning. Novel formulations of optimization problems for agent group control are proposed, and computer simulations for 100 agents are conducted. A set of criteria and metrics is introduced to evaluate algorithm performance, enabling conclusions about their applicability and alignment with simulation requirements. Based on the analysis of group control methods and environmental dynamics, recommendations are provided for centralized and decentralized approaches, as well as formation-based or cloud-like motion. A hybrid algorithm combining the potential field method and particle swarm optimization is proposed, achieving balanced motion characteristics for agent groups.

Keywords
Optimization, local navigation, autonomous robot group, swarm intelligence, agent

1. Introduction

The use of groups of mobile robotic systems (MRS) that can autonomously or semi-autonomously perform tasks is becoming increasingly widespread. Furthermore, the focus is gradually shifting from small teams of MRS to larger groups of agents controlled by artificial intelligence [1]. These tasks include the movement of goods in automated warehouses [2], chemical treatments [3], crop production and irrigation [4], and monitoring agricultural land, etc. The performance of tasks by groups of MRS agents for various technological areas requires the development of algorithms and methods for supporting the group's movement as a single control object, resistant to the action of different obstacles of various nature using local positioning algorithms [5, 6, 7].

The absence or insufficient accuracy of global positioning systems complicates the autonomous movement of a group of agents, which requires new approaches to local navigation. The development algorithms based on solving optimization problems that will ensure the autonomous movement of a group of agents using local positioning. In this case, it is necessary to consider the hardware limitations of systems using medium-performance computers. Global positioning systems: satellite or cellular can be jammed or intentionally turned off, be physically inaccessible in industrial buildings, or have insufficient accuracy for several applied tasks. The development of a meaningful statement of the problem of optimizing the movement of autonomous groups of agents with local positioning in a relative coordinate system will allow ensuring the efficiency of the movement of a group of MRS in a given topological form according to an adaptively selected movement criterion and without the need for a group leader, which is a relevant scientific and applied problem.

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To control a group of MRS, they are united in an Ad-Hoc network, which is based on the 802.11 or 802.15.4 standards, that allows to increase the reliability of control by retransmitting data packets and remote-control commands [8]. In case when the global positioning is unavailable, group of MRS must operate in a local (relative) coordinate system – to sustain mutual positioning and avoid potential collisions. This local coordinate system is the same for all MRS in a group but has no connection with the global positioning systems. For local positioning of agents in a relative coordinate system, the following are used: radio distance sensors, positioning data from cellular networks, global satellite positioning data, radio frequency markers, ultrasonic and infrared sensors, lidars, radars, etc., which face significant problems in environments with complex topology. Overloading of the radio frequency spectrum and multipath propagation and reflection degrade the performance of positioning using radio methods, while the radiophysical properties of satellite signals limit their effectiveness in urban areas, closed warehouses, etc. These signals may also be intentionally suppressed for security reasons or to ensure the privacy of citizens' personal lives. In these cases, local coordinate systems must be used, allowing to apply swarm algorithms to control MRS group movement.

The organization of the movement of a group of agents as a single whole is based on the use of several well-known approaches to controlling a collective of agents [8, 9, 10]: Vicsek algorithm, Reynolds algorithm (Boids), Potential Field Method (PFM), as well as Swarm Intelligence algorithms, for example, Particle Swarm Optimization (PSO) algorithm. In particular, there are combined solutions: Virtual Collaborative Network, Olfati-Saber's flocking algorithm [11], etc. These algorithms are based on the adaptive use of several algorithms depending on the movement conditions, for example, Reynolds algorithm for group movement without obstacles and the potential method for movement between physical obstacles that need to be avoided, as well as the application of Vicsek algorithm for group movement with a temporary leader in a dynamic environment that requires high speed of reaction to threats to the integrity of the group, for example, a flock of wild birds or predatory animals.

2. Key Issues Addressed in This Study

This research examines critical challenges associated with autonomous MRS operating under conditions of limited or inaccurate global positioning. The main aspects investigated include:

- The need for novel approaches to local navigation due to the absence or insufficient accuracy of global positioning systems.
- The development of a well-defined formulation of the movement optimization problem for autonomous groups utilizing local positioning, ensuring the effectiveness of control algorithms in maintaining a specified topological configuration.
- The introduction of a comprehensive set of criteria and metrics to assess algorithm performance, facilitating the evaluation of their applicability and suitability for simulation-based scenarios.
- Analyzing existing group control methods and environmental dynamics to formulate recommendations for both centralized and decentralized control strategies, as well as formation-based and cloud-like motion paradigms.

3. Principles of Group Movement Algorithms

Different approaches have been developed to define the movement rules for autonomous agent groups. This section examines key algorithms that shape multi-agent coordination.

Vicsek's algorithm [12] relies on three fundamental principles: separation, where agents avoid collisions with their neighbors; alignment, where they adjust their velocity to match the average speed of surrounding agents; and cohesion, where they maintain a certain distance from the local center of mass.

The Potential Field Method (PFM) [13] models agent movement using attractive and repulsive forces. Attractive potentials draw agents toward a target or their neighbors, promoting coordinated motion, while repulsive potentials push them apart when they come too close, preventing overcrowding and collisions.

Reynolds' algorithm [14], also known as the Boids model, follows the same three principles as Vicsek's: separation, to avoid collisions; alignment, to match speed and direction with neighbors; and cohesion, to stay near the center of mass of local agents. This model is widely used for simulating flocking and swarm behavior.

The Particle Swarm Optimization (PSO) [15] algorithm optimizes movement by balancing individual and collective experience. Each agent tracks its best-known position, while also receiving information from the group about optimal locations. Using this data, agents adjust their movement to improve efficiency and overall swarm performance.

The Cucker-Smale model [16] describes collective motion through dynamic interactions. Agents adjust their speed based on their distance to others, aiming for alignment with nearby agents and convergence toward a shared velocity over time. This algorithm is often used to study consensus formation in distributed systems.

The Virtual Structure method [17] maintains a predefined formation, such as a line or circle, by treating the group as a rigid geometric shape. Agents correct their positions based on deviations from this virtual structure, ensuring stable formation during movement. This method is particularly effective for tasks requiring precise spatial organization.

Behavior-Based Control [18] governs movement through a set of prioritized behavioral rules. Agents follow instructions such as collision avoidance, target pursuit, and formation maintenance, adapting dynamically based on situational demands. Decision-making is decentralized, with each agent acting based on local observations rather than centralized commands.

The choice of an appropriate control algorithm depends on how the MRS group is organized. Some strategies involve a fixed leader, others operate without leadership, and some rely on temporary leaders. Additionally, maintaining a stable formation or ensuring flexible spacing between agents influences algorithm selection. Effective coordination also requires keeping the group within a defined radius during movement and maneuvers.

4. Analysis of Decentralized Control Approaches for Group Movement

Decentralized control of multi-agent systems can be implemented through different strategies, each with distinct advantages and limitations. This section examines two primary approaches: leader-based control and leaderless coordination.

4.1. Leader-Based Approach

In this model, a designated leader determines the movement direction, while the remaining agents follow its trajectory [19]. This approach is commonly used in algorithms such as Vicsek's model.

A key advantage of this method is its simplicity—a single agent dictates movement, reducing the complexity of coordination. It also enables a fast response to dynamic changes, as the leader can make real-time decisions, such as obstacle avoidance. The approach enhances goal-oriented efficiency, making it easier for the group to reach a specific target location. Additionally, communication costs are lower, as agents primarily exchange data with the leader rather than continuously coordinating with multiple neighbors.

However, the method introduces a single point of failure—if the leader is lost, the group may become disorganized, at least temporarily. Scalability is also a challenge, as the leader may struggle to manage communication in larger groups. Moreover, reliance on a leader reduces flexibility, as the group's adaptability to unforeseen changes depends entirely on the leader's decision-making.

4.2. Leaderless Approach (Center of Mass Coordination)

An alternative model eliminates the need for a leader by basing movement decisions on the collective behavior of the entire group [20]. This is characteristic of algorithms such as Reynolds' Boids model and swarm-based approaches.

A key strength of this method is its robustness—without a central leader, the system avoids a single point of failure. The approach also supports scalability, as adding new agents does not disrupt overall coordination. Adaptability is another advantage, as each agent continuously adjusts its movement in response to local conditions, leading to emergent behaviors that enhance system resilience. Even when agents are lost, the group dynamically reorganizes itself, maintaining cohesion.

Despite these advantages, leaderless control presents challenges in goal-directed movement, as the absence of centralized coordination makes it harder to ensure that the group efficiently reaches a predefined objective. Communication costs are also higher, as agents must frequently exchange data to track their neighbors and determine the collective center of mass. Additionally, response times to large-scale environmental changes may be slower, as decision-making emerges from distributed interactions rather than a single directive source.

4.3. Comparison of Leader-Based and Leaderless Control

Table 1 summarizes the key differences between leader-based and leaderless movement strategies, highlighting their respective strengths and weaknesses. The choice between these approaches depends on the specific requirements of the system, including scalability, adaptability, and the need for centralized coordination.

Table 1
Comparison of methods for managing a group of agents in terms of stability and energy efficiency

Parameter	With the leader	Without a leader
Complexity	Low (centralized logic)	High (decentralized rules)
Scalability	Limited	High
Robustness	Low	High
Reaction speed	Fast	Slow (for global changes)
Energy efficiency	Higher (less calculations, less maneuvers)	Lower (frequent calculations, more frequent trajectory adjustments)

4.4. Summary of the Comparative Analysis of Leader-Based Control in MRS

The choice between leader-based and leaderless control in MRS group depends on factors such as group size, task objectives, and adaptability requirements.

- Leader-based control is most effective for small groups, tasks with a clear goal, or scenarios requiring a rapid response to dynamic threats. The centralized decision-making structure ensures efficiency in well-defined missions.
- Leaderless control is better suited for large-scale MRS groups, where resilience and adaptability are crucial. This approach is commonly used in drone swarms for applications like territorial monitoring, where decentralized coordination allows the system to function despite agent losses.

- Hybrid models, such as temporary leadership, offer a balance between these approaches, leveraging both centralized coordination and decentralized adaptability. However, these models often increase computational demands, as agents must process a larger volume of information to dynamically assign leadership roles.

Selecting the appropriate control strategy depends on mission requirements, system scalability, and computational capabilities.

5. Analysis of Group Movement in Formation and Amorphous Configurations

The movement of MRS group can be organized in two fundamental ways: formation-based movement, where agents maintain a structured geometric pattern, and amorphous movement, where agents move without a fixed shape. Each approach has distinct advantages and challenges, which are further influenced by the presence or absence of a leader.

5.1. Formation-Based Movement (Agents Positioned at the Vertices of a Geometric Structure)

In this approach [21], agents maintain predefined positions within a geometric configuration, such as a line, grid, or V-shape. This method is commonly used in applications like agricultural drone fleets, where precise coordination is necessary.

5.1.1. Advantages of Formation-Based Movement

Formation-based movement provides structured coordination, making it easier to control a group, especially when a leader is present to guide movement. This is particularly useful in applications such as convoys or synchronized drone operations. One of the major benefits is energy efficiency. Agents can take advantage of aerodynamic effects, such as drafting, where those positioned behind a leader experience reduced air resistance. This principle, commonly observed in bird formations, helps improve fuel or battery efficiency. Additionally, optimized routing reduces unnecessary maneuvers, minimizing overall energy consumption.

Another advantage is the ease of monitoring and tracking. Since agents follow a predictable structure, both visual and sensor-based supervision become more effective. This is crucial for applications requiring precise control over a fleet of robots or drones. Moreover, role distribution within the formation enhances coordination. A leader—or a set of designated assistant agents—dictates movement patterns, allowing the system to function more efficiently with predefined roles and responsibilities.

5.1.2. Challenges of Formation-Based Movement

However, this method comes with challenges. Maintaining a strict formation requires continuous communication and synchronization, often relying on virtual structure algorithms. In large groups, the leader can become a bottleneck, limiting data exchange efficiency. Additionally, formations struggle in dynamic environments; avoiding obstacles often disrupts the structure, requiring time and energy to restore it. Another limitation is the constant need for position adjustments, which increases energy consumption and can slow down overall movement efficiency. Despite these challenges, formation-based movement remains a preferred choice for tasks requiring structured coordination and precise execution.

5.2. Amorphous Movement (Similar to a "Mosquito Cloud")

In contrast to formation-based movement, amorphous movement involves agents that move without maintaining a fixed geometric structure [22]. This approach is often compared to the behavior of swarm intelligence, where agents exhibit flexible, decentralized decision-making, similar to a "cloud" of mosquitoes or insects.

5.2.1. Advantages of Amorphous Movement

One of the key benefits of amorphous movement is flexibility. The system can easily adapt to unforeseen obstacles or dynamic environments, as agents make decisions based on local rules and interactions with their neighbors. This approach allows for quick adjustments without the need for complex coordination. Additionally, the system is robust because it does not rely on any single agent. If one agent fails or is lost, the rest of the group can continue functioning effectively.

Amorphous movement also has low communication requirements compared to formation-based systems. Since agents follow simple local rules, such as those outlined in Reynolds' algorithm, the need for constant communication is minimized. Agents only need to exchange minimal information, typically about the position and movement of nearby agents, rather than relying on centralized commands or constant updates.

5.2.2. Disadvantages of Amorphous Movement

However, amorphous movement comes with certain drawbacks. One of the main disadvantages is higher energy consumption on average. Due to the lack of a structured formation, agents often need to perform more frequent maneuvers to avoid collisions with one another. These constant adjustments can lead to increased energy use.

Additionally, there is a lack of global route optimization in this approach. Without a fixed structure or centralized control, the group does not have an optimized path for the entire swarm, leading to potential inefficiencies in movement. Achieving a global goal (such as reaching a specific destination) can also be more challenging, as the group’s movement is decentralized and may take longer compared to formation-based systems.

While amorphous movement offers greater flexibility and robustness, it requires a trade-off in terms of energy efficiency and global coordination.

Table 2 compares the movement process of MRS group in formation and amorphous form in terms of energy spending on movement along the route and keeping the group together.

Table 2
The influence of the MRS group formation on the mechanical energy consumption when moving a group of agents

Factor	Movement in formation	Amorphous movement
Energy efficiency on the route	Higher (route optimization)	Lower (frequent maneuvers)
Agents position control costs	High (position correction)	Low (local rules execution)

5.3. Communication and Spatial Coordination

Effective communication and spatial coordination are critical in determining the efficiency and performance of both formation-based and amorphous movement. These approaches require different methods of information exchange and control strategies.

5.3.1. Formation Movement

In formation-based movement, agents rely on constant position data exchange, often facilitated by consensus algorithms. These algorithms ensure that all agents stay in sync with each other and maintain their designated positions within the formation. The system typically uses a global coordinate system, which allows for precise control over the group's overall position and movement relative to a fixed reference frame. This structured approach ensures high coordination but demands regular communication, especially as the group size increases.

5.3.2. Amorphous Movement

In contrast, amorphous movement relies on local data exchange. Each agent interacts with its immediate neighbors, typically within a defined "visibility radius". This limits the communication range, allowing agents to operate with minimal data exchange. The system is governed by decentralized control, where decisions are made based on local interactions. Algorithms like Boids use simple rules of separation, alignment, and cohesion, allowing agents to move efficiently without needing global coordination. This decentralized approach enables higher flexibility but sacrifices some global coordination and optimization.

Table 3 provides a comparative analysis of the communication and coordination requirements for agents moving in formation versus in an amorphous configuration. It summarizes the differences in communication strategies and control models, highlighting the trade-offs between structured coordination and decentralized adaptability.

Table 3
Comparative table of characteristics of the movement of agents in formation and amorphous form

Characteristic	Movement in formation	Amorphous movement
Structure of hierarchy	High	Low
Route energy efficiency	High	Low
Formation control costs	High	Low
Communication level	Intense	Minimum
Flexibility in dynamic environments	Limited	High
Robustness	Low	High
Route optimization	Global	Absent
Monitoring	Simple	Complicated
Role distribution	Centralized	Decentralized
Leader influence	Decisive	Absent
Difficulty avoiding obstacles by maneuvering	High	Low
Group movement speed	Average	High

Summary of the comparative analysis. Formation is effective in stable environments with clear goals (e.g., agricultural drones [2, 4), but ineffective in unpredictable changes. Amorphous movement is better suited for dynamic environments (e.g., urban research) where adaptability is important, but may be less economical.

6. Using kinetic and potential energy data for agent group motion control models

The authors consider, that for modeling the motion of a group of MRS with known agent masses, it is important to take into account the values of the average and maximum kinetic and potential mechanical energy of the agents in the group during its movement, as well as to study the probability of collisions of agents in conditions when the coordinates and distances between them are measured with errors. Several scientific works are aimed at the study of potential and kinetic energy during uniform rectilinear motion of MRS groups, as well as the probability of collisions between group members [11, 23-27].

In the article [28], an accurate energy consumption model for a certain topology of a UAV flock is discussed, which takes into account different flight modes (up, down, inclined and horizontal). This model aims to optimize the global energy consumption during the formation process of UAV swarms, although it does not separately analyze potential and kinetic energy in the context of uniform rectilinear motion. In [25], an energy-efficient algorithm for optimizing data acquisition for UAV swarms is investigated. The algorithm focuses on data transmission efficiency and energy consumption during operations and does not directly address the average and maximum values of potential and kinetic energy during movement. In [23], a comprehensive review of UAV swarm formation control is performed, describing various swarm formation strategies, including those that use artificial potential fields. This review considers the dynamics of swarm behavior but does not delve into specific energy metrics associated with uniform rectilinear motion.

7. Collision Probability Research

Review [23] focuses on motion control and group formation maintenance, analyzes collision avoidance strategies in UAV groups. An article [23] also discusses centralized, decentralized, and behavior-based methods for maintaining a safe distance between agents, but lacks a specific quantitative analysis of collision probabilities. An article [26] studies reinforcement learning-based formation locking and shows that drones learn to avoid collisions by coordinating their movements. This implies a probabilistic framework for collision avoidance but does not provide explicit metrics for collision probability.

Review [28] provides a theoretical framework for designing algorithms for flocking and reviews the dynamics of multi-agent systems, including collision avoidance mechanisms. However, the review is mainly focused on algorithmic design rather than empirical studies of collision probabilities. Considering the magnitudes of potential and kinetic energy, as well as their average and maximum values for a group of agents and understanding the dynamics of energy allows you to develop more efficient flight trajectories, minimizing unnecessary energy consumption. This is crucial for extending the flight range of UAVs, especially in group formations, where collective energy savings can be significant [29, 30].

The following relationships can be used to calculate the average and maximum values of potential and kinetic energy for a group of agents. Kinetic energy is calculated from the speed of the agents (the square of the magnitude of the velocity vector). Potential energy is determined from the height of the agent in the gravitational field.

Average kinetic energy (average of kinetic energy of all agents):

$$\bar{E}_k = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{2} m \left\| \vec{v}_i \right\|^2, \tag{1}$$

where N – is the number of agents, m – is the mass of the agent, and $\left\| \vec{v}_i \right\|$ – is the speed of the i-th agent.

Maximum kinetic energy (maximum value among all agents):

$$E \max_{1 \le i \le N} \left(\frac{1}{2} m \|\vec{v}_i\|^2 \right)_{kmax} \tag{2}$$

Average potential energy (average potential energy of all agents):

$$\bar{E}_p = \frac{1}{N} \sum_{i=1}^{N} mg\, h_i , \tag{3}$$

where g – is the acceleration of free fall, h_i – is the height of the i-th agent, for the two-dimensional case $h_i = y_i$ – is the coordinate.

Maximum potential energy (maximum value among all agents):

$$E \max_{1 \le i \le N} \left(m \cdot g \cdot h_i \right)_{p\,max} \tag{4}$$

These formulas are used to calculate the energy of agents in a simulation, allowing for the evaluation of their dynamics and interactions.

Research [29] demonstrates that drones flying in coordinated formations can save up to 70% of their energy compared to individually controlled drone swarms. By analyzing potential and kinetic energy, swarm algorithms can be improved to support formations that maximize energy efficiency during operations. For a small group of MRS, it is important to know the maximum and average potential and kinetic energies of the agent and group. Estimates of potential energies associated with the positions of drones in the swarm allow algorithms to better predict and prevent agent collisions. This approach increases safety and reliability in complex environments where multiple MRS operate simultaneously [30].

Knowledge of kinetic energy helps drones make informed decisions in real time about speed and maneuverability, allowing them to dynamically adjust trajectories to avoid obstacles and other drones, thus reducing the likelihood of collisions [31]. Analyzing energy metrics helps determine how much payload a drone can carry without exceeding its energy limit. This is especially important in missions where drones are needed to transport supplies or transmit data [28-29]. Understanding how potential and kinetic energy change with changing environmental conditions (e.g., wind or terrain) allows for the development of adaptive strategies that improve overall mission performance [28]. Predicting the dynamics of energy changes allows for better strategic mission planning, allowing swarm leaders to effectively allocate tasks among drones based on their energy state and capabilities [28].

By optimizing energy consumption by incorporating kinetic and potential energy into the movement algorithms, drone swarms can operate more stably over long periods of time, i.e., provide long-term stability of movements, which is important for environmental monitoring or disaster response, where continuous operation may be required [29, 31].

Thus, integrating potential and kinetic energy analysis into drone swarm operations not only improves efficiency and safety, but also contributes to more effective task performance and stability in the previously listed control models. In summary, although there are many studies on energy consumption patterns and collision avoidance strategies in UAV swarms, only a few studies have focused on the average and maximum values of potential and kinetic energy during uniform rectilinear motion, as well as a detailed analysis of collision probabilities between swarm members. However, the available analysis results are limited or are clearly not considered in the current scientific literature. Further empirical research and computer simulations may be needed to fill these knowledge gaps.

8. Meaningful optimization problem statements for controlling a group of drones

Let us consider meaningful optimization problem statements for several approaches to control a group of drones to determine the required data set and the possibility of movement in a formation without a leader. Let us assume that the data on the global geographic coordinates of the drone are unknown, but all pairwise distances and all pairwise angles between all drones in the group are known. Combining the obtained algorithms will allow us to create an adaptive meta-algorithm for drone movement, which will combine the advantages of the algorithms combined in it.

Specific examples of situations, when this optimization problem should be used:

- MRS group should deliver a set of cargos of different weight/size in the urban surroundings, where global positioning is partially unavailable (in certain areas) due to security limitations.
- MRS group should provide sensors' checks on a regular basis (for example, to control speed of crops grow or presence/absence of pests) on a distant field (for example, in the mountains), where global positioning may be unavailable.
- MRS group should provide irrigation on a regular basis on a distant field (for example, in the mountains), where global positioning may be unavailable.

8.1. A meaningful formulation of group drone movement optimization problem based on the Vicsek Model

A meaningful statement for group movement according to the Vicsek Model can be formulated as an optimization problem, which consists in the coordinated movement of a group of drones in a given direction.

8.1.1. Problem description

A system with N drones moving in a two-dimensional space with a constant velocity v_0 is considered. Each drone updates its direction of movement, focusing on its neighbors within a certain interaction radius r, and considers the pairwise angle $\theta_{ij}(t)$ between drones i and j for more accurate orientation. The objective function should minimize the deviation of the drones' directions of movement from the average direction of their neighbors of an anti-imitation recognition mode.

8.1.2. Variables

t – designation of the next discrete moment in time in the model t = 0, 1, 2, ...

$v_i(t)$ – direction of movement of the i-th drone at time t.

$r_i(t)$ – position of the i-th drone in the local coordinate system at the moment of time t.

$\eta_i(t)$ – random noise, which characterizes the errors in measuring the direction of movement of the i-th drone.

$d_{ij}(t) = \| r_i(t) - r_j(t) \|$ – pairwise distance between drones i and j at time t.

$\theta_{ij}(t)$ – pairwise angle between the velocity vectors of drones i and j at time t.

$$\cos\left[\theta_{ij}(t)\right] = \frac{v_i(t) \cdot v_j(t)}{\|v_i(t)\| \|v_j(t)\|} \tag{5}$$

Including pairwise angles $\theta_{ij}(t)$ in the model allows drones to more accurately orient themselves to their neighbors, which improves the stability of movement and group cohesion. It also helps to reduce the chaotic nature of movement and more effectively form the structure of the drone group.

8.1.3. Objective function

$$J = min \sum_{i=1}^{N} \left\| v_i(t+1) - \frac{\langle v_j(t) \rangle_{d_{ij}<r,\theta_{ij}} + \eta_i(t)}{\left\| \langle v_j(t) \rangle_{d_{ij}<r,\theta_{ij}} + \eta_i(t) \right\|} \right\|^2 \tag{6}$$

minimizes the root mean square deviation of the drones' directions from the average direction of their neighbors, considering pairwise angles.

8.1.4. Constraints

$\| v_i(t) \| = v_0$ – the norm of the velocity vector of each drone is a constant value, i.e. all drones move at the same speed, but can change the direction of movement. This is a key condition of the Vicsek model: drones do not accelerate or decelerate but only adjust the direction of movement based on interaction with neighbors and random disturbances.

$r_i(t)$ – is within the permissible limits of the movement area, i.e. each drone considers the distances to drones within a radius of r:

$$\langle v_j(t) \rangle_{d_{ij}<r,\theta_{ij}} = \frac{1}{|S_i|} \sum_{j \in S_i} v_j(t) \cos[\theta_{ij}(t)], \tag{7}$$

where $S_i = \{ j \mid d_{ij} < r\}$ is the set of neighbors of the i-th drone.

8.1.5. Updating the speed and position

The direction of the drone at time t+1 is updated according to the rule:

$$v_i(t+1) = \frac{\langle v_j(t) \rangle_{d_{ij}<r,\theta_{ij}} + \eta_i(t)}{\left\| \langle v_j(t) \rangle_{d_{ij}<r,\theta_{ij}} + \eta_i(t) \right\|} \tag{8}$$

The drone position at time t+1 is updated according to the formula:

$$r_i(t+1) = r_i(t) + v_0 \cdot v_i(t+1) \cdot \triangle t, \tag{9}$$

where Δt – is a small-time step that determines how far the drone will move in one update cycle, i.e. Δt – is a continuous time interval. It can be fractional, for example, 0.1 seconds, and determines how much time passes between discrete moments t and t+1.

8.2. A meaningful formulation of group drone movement optimization problem based on the Reynolds model

A meaningful statement for group drone movement optimization problem based on the Reynolds model can be formulated as: a group of N drones in two-dimensional space is considered. The pairwise distances d_{ij} and angles θ_{ij} between the drones are known. The goal is to minimize the dispersion of the drones while preserving the group structure, matching the velocities, and avoiding collisions.

8.2.1. Objective function

Minimize the sum of the squared deviations of the drone positions from the local centers of mass:

$$J = min \sum_{i=1}^{N} \sum_{j \in N_i} \| r_i - r_{cent,i} \|^2, \tag{10}$$

where $r_{cent,i} = \frac{1}{|N_i|} \sum_{j \in N_i} r_j$ is the center of mass of the neighbors of the i-th drone, N_i is the set of indices of the neighbors of the i-th drone in the neighborhood with radius R, $|N_i|$ is the cardinal number, the cardinality of the set N_i, the number of elements in the set N_i.

8.2.2. Dynamics of drone state changes

Now let's consider how speed update, limits and position update should be taken into account. Speed update:

$$v_i^{t+1} = v_i^t + \underbrace{k_1\left(v_{avg,i} - v_i^t\right)}_{\alpha} + \underbrace{k_2 \sum_{j \in N_i} \frac{r_i - r_j}{d_{ij}^2}}_{\varepsilon} + \underbrace{k_3\left(r_{cent,i} - r_i^t\right)}_{\gamma}, \tag{11}$$

where α is a drone alignment, ε is a drone separation, and γ is a drone cohesion,

$$v_{avg,i} = \frac{1}{\left|N_i\right|} \sum_{j \in N_i} v_j \tag{12}$$

Speed limits:

$$\left\|v_i^{t+1}\right\| \leq v_{max} \tag{13}$$

Update the position:

$$r_i^{t+1} = r_i^t + v_i^{t+1} \triangle\ t \tag{14}$$

8.2.3. Limitations

Now let's consider problem's limitations. They include collision avoidance and preservation of structure. Collision avoidance:

$$Dij \geq dmin,\ \forall\ i \neq j \tag{15}$$

Preservation of structure:

$$\left|\theta_{ij}^t - \theta_{ij}^0\right| \leq \delta_0,\ \forall\ i, j \tag{16}$$

where θ_{ij}^0 is the initial angle between drones i and j, θ_{ij}^t is the current angle between drones i and

Solving the problem potentially provides optimal control of: cohesion, synchronization, and safety of drone movement in a relative coordinate system using: nonlinear constraints, local interactions, and balancing between drone interests.

8.3. A meaningful formulation of group drone movement optimization problem based on Potential Fields Method

A meaningful statement for group drone movement optimization problem based on Potential Fields Method with unknown global coordinates. Objective: to develop an algorithm that will allow a group of drones to move to given targets, avoiding obstacles, using the potential method, using only pairwise distances and angles between drones. Input data:

For drones:

N – number of drones.

d_{ij} – distance between drones i and j.

θ_{ij} – angle between drones i and j.

For obstacles:

M – number of obstacles.

$x_{obs,j}$ – position of j-th obstacle.

$\rho_{0,j}$ – radius of influence of j-th obstacle.

For model parameters:

ξ – coefficient of attraction force.

η – coefficient of repulsion force.

A group of N drones is considered, moving towards the target points, avoiding obstacles, using only pairwise distances and angles between them. The potential field model generates attractive and repulsive potentials that control the movement of the group of drones. The attractive potential directs the drones towards the target, while the repulsive potential repels them from obstacles. The goal is to minimize the total potential energy of the system:

$$J = min \sum_{i=1}^{N} \left[U_{attr,i} + \sum_{j=1}^{M} U_{rep,ij} \right], \tag{17}$$

where $U_{attr,i}$ is the function describing the field of attraction to the target; $U_{rep,ij}$ is the function describing the field of repulsion from obstacles.

8.3.1. Functions describing potential fields

Gravity field:

$$U_{attr,i} = \frac{1}{2} \xi \left\| x_i - x_{g,i} \right\|^2, \tag{18}$$

where x_g – position of the goal.

Repulsion field from obstacles:

$$U_{rep,ij} = \begin{cases} \frac{1}{2} \eta \left(\frac{1}{\left\| x_i - x_{obs,j} \right\| - \frac{1}{\rho_{0,j}}} \right)^2, \left\| x_i - x_{obs,j} \right\| \le \rho_{0,j} \\ 0, \left\| x_i - x_{obs,j} \right\| > \rho_{0,j} \end{cases} \tag{19}$$

8.3.2. Drone Positions Update

The total force acting on the drone F_{tot} is:

$$F_{tot,i} = - \nabla U_{attr,i} - \sum_{j=1}^{M} \nabla U_{rep,ij} \tag{20}$$

Speed and position updates:

$$\begin{gathered} v_i(t + \triangle t) = v_i(t) + \alpha F_{tot,i} \\ x_i(t + \triangle t) = x_i(t) + v_i(t + \triangle t) \cdot \triangle t, \end{gathered} \tag{21}$$

where α is the force scaling factor.

8.3.3. Constraints

The drone speed is limited by the maximum speed: $\| v_i \| \le v_{max}$.

The distances between drones and obstacles must exceed critical values.

Collision avoidance rules:

- Drones must not intersect with each other.
- Drones must not intersect with obstacles.

8.3.4. Solution methods

Optimization may be performed using gradient descent or swarming methods (PSO, Boids). Dynamic position updates are based on local drone interactions without global coordinates.

The presented model allows drones to reach targets while avoiding obstacles using only local distance and angle measurements.

8.4. A meaningful formulation of group drone moment optimization based on Particle Swarm optimization algorithm

A meaningful statement for group drone moment optimization based on Particle Swarm optimization algorithm can be formulated as: optimization of the movement of a group of drones without global coordinates. The problem of optimal movement of a group of drones in a relative coordinate system is considered. The input data include pairwise distances and angles between drones.

8.4.1. Mathematical model

Let N drones move in a two-dimensional space, where:

d_{ij} is the pairwise distance between drones i and j.

θ_{ij} is the relative angle between drones i and j.

The updating of the velocities and positions of drones is carried out according to the law:

$$v_i(t+1)=\omega v_i(t)+c_1 r_1 (p_i-x_i(t))+c_2 r_2 (g-x_i(t))$$
$$x_i(t+1)=x_i(t)+v_i(t+1) \cdot \triangle t, \tag{22}$$

where ω is the inertia coefficient; c_1, c_2 are the learning coefficients; r_1, r_2 are random variables that have a uniform distribution on the interval [0, 1]; p_i is the best personal position of the drone, g is the best global position of the group. The velocity vector $v_i(t+1)$ contains both the direction and the magnitude of the movement in one step. Adding the velocity $v_i(t+1)$ to the position changes the coordinates of the drone $x_i(t)$ according to its movement.

8.4.2. Updating the personal drone and the global experience of the group

p_i is updated if $x_i(t+1)$ is better.

g is updated if $x_i(t+1)$ is better.

The objective function minimizes the average deviation of the drones from the given formation:

$$J=\sum_{i=1}^{N} \sum_{j=1, j\neq i}^{N} \left(\|x_i-x_j\|-d_{ij}\right)^2 \tag{23}$$

8.4.3. Solution methods

The algorithm for optimizing the movement of drones with unknown global coordinates uses local information to achieve optimal solutions, while remaining effective in finding global optima.

The following algorithms can be used for optimization:

- Locally-oriented swarm (general updating of trajectories based on interactions between drones).
- Hybrid methods (combination of Boids, PSO and potential field for coordinated movement).

The proposed approach provides robustness to the absence of global coordinates and efficiency in forming given configurations.

8.5. Optimization of collective motion of drones in a relative coordinate system

Collective drone movement in a relative coordinate system or locally oriented (LO) movement refers to an approach to drone movement coordination in which each drone makes decisions based only on local information, i.e. distances and angles to its nearest neighbors, without access to global coordinates. This is an approach similar to the Boids model, where drones interact through local rules for alignment, attraction, and collision avoidance. LO MRS group usually does not require a leader, since movement decisions are made individually by each drone based on local information. To speed up the response to movement obstacles or to complicate communication between drones, the concept of a global landmark can be introduced, playing the role of a generalized "leader", which is determined decentralized through local decisions of drones. The rules of movement and interaction of drones in a locally oriented swarm can be defined by analogy with the Reynolds (Boids) model, but with significant differences due to the lack of global coordinates. In a locally oriented swarm, where drones only have information about distances d_{ij} and angles θ_{ij}, these rules can be modified as follows:я

- Alignment is based on comparing the relative angles of neighbors θ_{ij}, not absolute velocities.
- Homogeneity is defined as minimizing deviations from given distances d_{ij}.
- Repulsion takes into account local measurements to avoid clusters.

8.5.1. Problem formalization

Let's formalize this problem. A system of *N* drones in a two-dimensional space without a global coordinate system is considered. Each drone *i* has access to local data:

d_{ij} – desired distance from drone *i* to drone *j* (defined by the target formation).

θ_{ij} – desired relative angle to drone *j* in its own coordinate system.

Now we are ready to formulate the mathematical model.

Firstly, lets show in detail local coordinate system of the drone. For drone *i*, the position of neighbor *j* in its coordinate system is given as:

$$x_{j|i}=d_{ij}\begin{bmatrix}\cos\theta_{ij}\\ \sin\theta_{ij}\end{bmatrix} \quad (24)$$

The current position of *j* relative to *i* is determined by measuring:

$$\tilde{x}_{j|i}=\tilde{d}_{ij}\begin{bmatrix}\widetilde{\cos\theta}_{ij}\\ \widetilde{\sin\theta}_{ij}\end{bmatrix}, \quad (25)$$

where $\tilde{d}_{ij}$, $\tilde{\theta}_{ij}$ are real measurements.

Objective function is to minimize the total deviation from the desired formation:

$$J=\sum_{i=1}^{N}\sum_{j\in N_i}\left(\left\|\tilde{x}_{j|i}-x_{j|i}\right\|^2+\lambda\cdot\left[\angle\left(\tilde{x}_{j|i},x_{j|i}\right)\right]^2\right), \quad (26)$$

where N_i is the set of neighbors of drone *i*, λ is the weighting factor for the angular deviation, $\angle\left(\tilde{x}_{j|i},x_{j|i}\right)$ is the angle between the vectors.

Drone dynamics is measured by the update of the speed of drone *i*, which is based on local information:

$$v_i(t+1)=\omega\cdot v_i(t)+c_1\sum_{j\in N_i}\left(x_{j|i}-x_{j|i}\right)+c_2\sum_{k\in N_i}\phi\left(\left\|x_{ik}\right\|\right)\cdot x_{ik}, \quad (27)$$

where $\phi\left(\left\|x_{ik}\right\|\right)$ – potential function for collision avoidance (e.g., $\phi(r)=\frac{1}{r^2}-\frac{1}{r_0^2}$ for $r<r_0$, $x_{ik}=x_k-x_i$– vector from *i* to *k* in the global system (immeasurable directly, but approximated through local transformations).

Constraints in the problem formulation could be formalized as:

$$\left\|v_i\right\|\le v_{max}, \quad (28)$$

$$\left\|x_i-x_j\right\|\ge d_{sa};i\ne j. \quad (29)$$

8.5.2. Optimization approaches

First approach to the search of optimized solution is usage of decentralized gradient descent. Each drone updates its position by minimizing the local component J_i:

$$x_i(t+1)=x_i(t)-\eta \cdot \nabla_{x_i} J_i, \tag{30}$$

where η is the learning step, $\nabla_{x_i} J_i$ calculated through the Jacobian of the transformation between local and global coordinates.

Second approach, that could be used – consensus algorithm. To agree on the global formation, iterative updating is used:

$$x_i(t+1)=x_i(t)+\sum_{j\in N_i} \alpha_{ij}\left(x_j(t)-x_i(t)\right), \tag{31}$$

where α_{ij} are weights depending on the formation error.

But we would propose to use another, integrative approach for this optimization problem – Optimization of Collective Motion (OCM). Advantages of the proposed OCM approach:

- Consideration of both distances and angles in the objective function.
- Use of exclusively local data without global coordinates.
- Explicit modeling of collision avoidance through potential fields.
- Decentralized optimization, ensuring scalability.

This description provides a more rigorous mathematical framework, explicitly considers constraints and local interactions, and does not use the assumption of availability of global information.

9. Development of criteria for assessing the quality of drone group control simulation

The following metrics can be used to assess the performance of algorithms or methods for keeping a group of drones in a given area while moving.

9.1. Average distance between drones $\bar{L}$

The metric allows you to assess how close the drones are to each other, i.e. the cohesion of the drone team:

$$\bar{L}=\frac{1}{N(N-1)}\sum_{i=1}^{N}\sum_{j=1,j\neq i}^{N}\left\|p_i-p_j\right\|, \tag{32}$$

where p_i and p_j are the positions of drones i and j, and N – is the total number of drones.

9.2. Maximum distance between drones Lmax

The metric allows you to determine the degree of distance between drones from the flock. A smaller value means better cohesion of the drone group:

$$L\max_{i,j}\left\|p_i-p_j\right\|_{max} \tag{33}$$

9.3. Average deviation from target position σ

The metric allows you to assess how well the drones maintain their target position in the formation. A smaller deviation value indicates better formation stability:

$$\sigma = \frac{1}{N} \sum_{i=1}^{N} \left\| p_i - o_i \right\|, \tag{34}$$

where o_i – is the target position of drone i.

9.4. Number of collisions *C*

The metric allows you to assess the degree of effectiveness of avoiding collisions by drones. A smaller number of drone collisions indicates better performance of the algorithm:

$$C = \sum_{i=1}^{N} \sum_{j=1, j \neq i}^{N} 1\left(\left\| p_i - p_j \right\| < d_{min}() \right), \tag{35}$$

where d_{min} – is the minimum allowable distance between drones, and 1(.)– is an indicator function, that is equal to "1", if the condition is met and equal to "0" – otherwise.

9.5. Average drone speed $\bar{S}$

The metric allows you to estimate how fast the drones of the group are moving. The optimal speed value may depend on the specific task:

$$\bar{S} = \frac{1}{N} \sum_{i=1}^{N} \left\| v_i \right\|, \tag{36}$$

where v_i – is the speed of drone i.

9.6. Formation stability *F*

The metric allows us to assess the stability of drones maintaining the formation. A smaller value of the deviation of drones from the target formation indicates better stability:

$$F = \frac{1}{T} \sum_{t=1}^{T} \frac{1}{N} \sum_{i=1}^{N} \left\| p_i(t) - o_i(t) \right\|, \tag{37}$$

where T – is the number of simulation steps, $p_i(t)$ and $o_i(t)$ are the measured position and target position of drone i at step t.

9.7. Energy efficiency *E*

The metric shows the energy consumption per unit distance by a group of drones to maintain formation movement. A smaller energy consumption value indicates a better performance of the algorithm:

$$E = \frac{1}{N} \sum_{i=1}^{N} \int_{0}^{T} \left\| a_i(t) \right\|, \tag{38}$$

where $a_i(t)$ – acceleration of drone i at step t.

Let us summarize the theoretically achievable results of the movement of a group of drones in formation using different methods and algorithms in Table 4.

For the algorithms and methods listed in Table 4, a simulation was performed for 100 drones with an average of 1000 launches with random initial positions.

The simulation results are summarized in Table 5 and Table 6. The average speed of the drones is fixed. The simulation time was approximately 11 minutes in the free colab.google environment.

Table 4
Comparison of algorithms for keeping drones in a group during movement based on their theoretically achievable indicators

Metrics	Vicsek	Boids	PSO	PFM	OCM
Average distance between drones	Average	Average	High	High	Average
Maximum distance between drones	High	Average	Average	Average	Average
Average deviation from target position	High	Average	Low	Low	Low
Number of collisions	Low	Low	Low	Low	Low
Average drone speed	Average	Average	High	High	Average
Formation stability	High	High	High	High	High
Energy efficiency	Average	High	High	High	High

Table 5
Simulation results for algorithms and methods in absolute values

Metrics	Vicsek	Boids	PSO	PFM	OCM
Average distance between drones	277.26	414.96	3.14	127.39	14.47
Maximum distance between drones	1120.33	1150.81	7.82	285.11	42.89
Average deviation from target position	191.71	401.76	2.36	487.78	224.65
Number of collisions	157.0	6.0	4366.0	72.0	416.0
Average drone speed	0.6	0.6	0.6	0.6	0.6
Formation stability	0.05	0.02	0.81	0.02	0.04
Energy efficiency	0.02	0.01	0.46	0.04	0.25
Average kinetic energy	0.18	0.18	0.18	0.18	0.18
Maximum kinetic energy	0.18	0.18	0.18	0.18	0.18
Average potential energy	932.68	1835.72	242.73	528.54	248.24
Maximum potential energy	5936.22	5979.45	280.89	1350.67	409.96

Table 6
Comparison of algorithms for keeping drones in a group during movement based on simulation results

Metrics	Vicsek	Boids	PSO	PFM	OCM
Average distance between drones	Average	*High*	*Low*	*Average*	*Low*
Maximum distance between drones	High	*High*	*Low*	Average	*Low*
Average deviation from target position	*Average*	*High*	Low	*High*	*Average*
Number of collisions	*Average*	Low	*High*	Low	*Average*
Average drone speed	Fixed speed value				
Formation stability	High	High	*Low*	High	High
Energy efficiency	*High*	High	*Low*	High	*Low*

Comparison of theoretical results for drone swarming algorithms with simulations based on qualitative metrics is shown in Table 7.

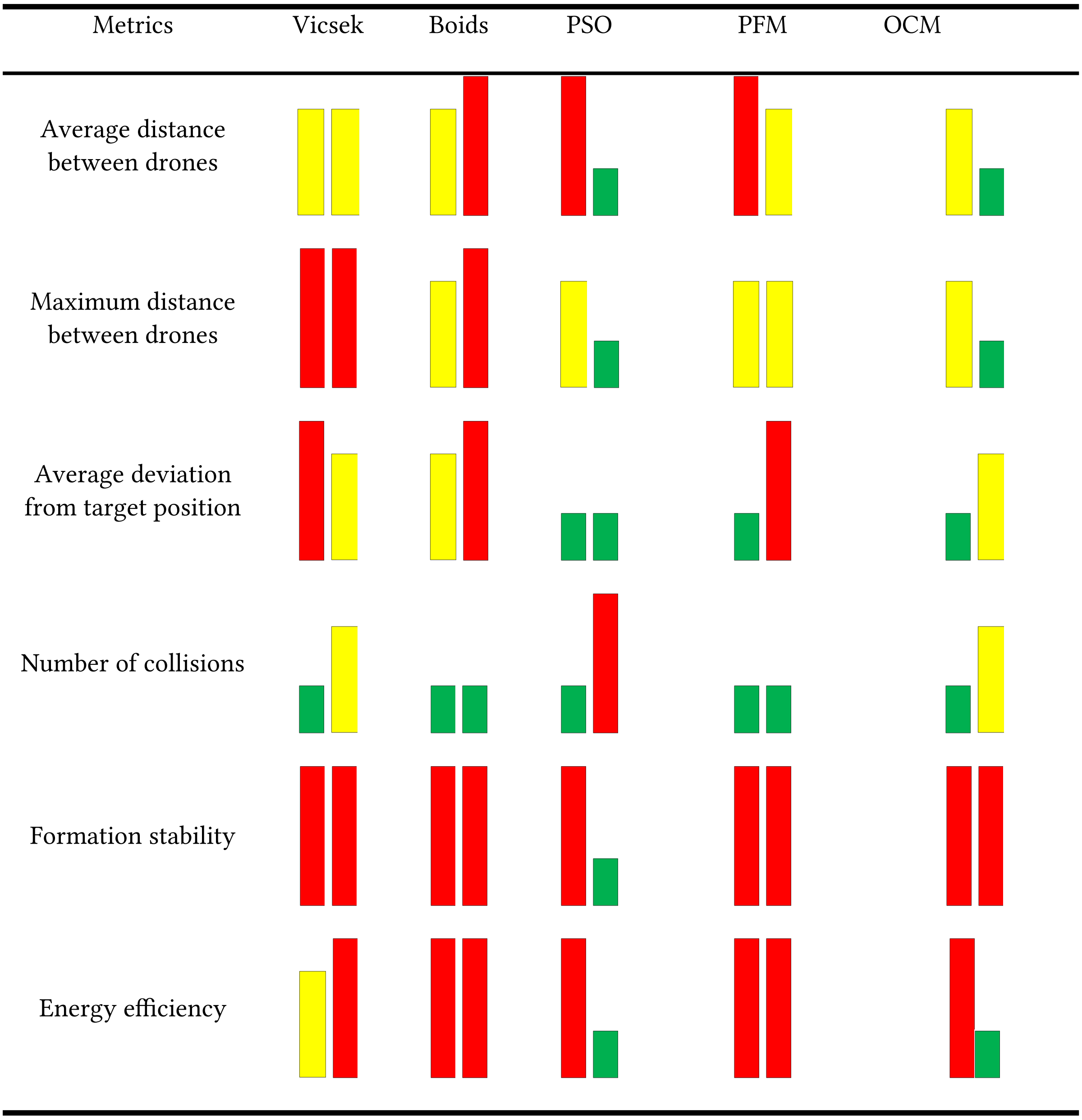
OCM and PSO theoretically possess high energy efficiency, which was evaluated based on the analysis of several scientific papers (Table 4) for simulations where a global coordinate system is available. Simulation in a local coordinate system (Table 5, Table 6) shows their low energy efficiency.

Comparison of the indicators in Table 4 and Table 6 demonstrates the correspondence of the experimental data to the theoretical indicators, which is 13/28 (46.3%). "Collision" is understood as the approach of drones to a distance less than the established limit in the optimization problem formulation. The evaluation parameter "number of collisions" shows the need to equip drones with proximity sensors that will solve the collision problem by reflex methods when the mathematical control algorithm does not find an optimal solution. At a fixed average speed and random values of the drone positions, i.e. in the absence of movement along the trajectory, estimates of the maximum and average kinetic energy of drones and their groups do not provide additional information, but in more complex motion models the results will be different.

A qualitative comparison of theoretical results (from scientific publications) for drone swarming algorithms using global coordinates with simulations for drone swarming algorithms using local coordinates and moving at a constant speed showed differences in some metrics (Table 7). There is a decrease in energy efficiency for complex methods, an increase in the number of collisions, the need to reduce the distance between drones and the speed of the group to keep the flock together when using only pairwise distances and angles between drones for navigation. This deterioration in the performance of the algorithms is expected when moving from global positioning to local positioning.

An OCM algorithm combining PSO and PFM is proposed. A methodology for assessing the energy efficiency of agent motion is developed. Computer modeling and comparison with existing algorithms are performed. The OCM showed average results for all criteria, which indicates its balance. Experimental results for PSO showed a higher number of collisions (4366) than theoretically expected, which may be due to the sensitivity of the algorithm to the initial conditions. PSO is the worst in collision avoidance and has the worst energy efficiency. PFM provides good adaptation to obstacles.

Table 7
Comparison of theoretical results for drone swarming algorithms with simulations based on qualitative metrics



Actual physical experiments were conducted using four drones. The correlation between the obtained results from the field experiments and the simulations reached 85% agreement.

Directions for further development may be the study of methods for adapting to noise and sensor errors and tuning the algorithms for real-time scale and operation on limited computing resources. The program code of the algorithms used in the study is available at [32].

10. Conclusions

For the first time, meaningful statements are proposed for algorithms and methods used for modeling and controlling groups of agents in a relative coordinate system. This locally-centric coordinate system uses data on pairwise distances between drones and pairwise angles between the directions of the drone velocity vectors to position the drones of the group. New mathematical formulations of optimization problems for five algorithms (Vicsek, Boids, PSO, PFM, OCM) have been developed, which take into account only local data – pairwise distances and angles and do not require global positioning.

A hybrid algorithm has been proposed – optimization of collective drone movement in a relative coordinate system, which combines the advantages of PSO and PFM. A set of criteria for assessing the quality of work of algorithms and swarm intelligence methods for a group of drones has been formulated and a comparison of algorithms has been performed, which showed the balance of estimates for the OKR algorithm for collision prevention, the best algorithm according to this important criterion and parameter is PFM.

Algorithms and methods for modeling drone groups are based on setting from three to five basic parameters, therefore, deriving them into constraints, penalties, conditions and objective functions simplifies the calculation of the optimal solution, which is first proposed in the work. That is, instead of adjusting the simulation parameters or control by selection, it is proposed to calculate them for the main solutions of the optimization problem.

Known algorithms (four basic methods and swarm modeling algorithms Vicsek, Boids, PSO, PFM, etc.) can be modified to solve the problem of moving a group of drones without a leader in a relative coordinate system, as well as adapted to the problem of local positioning based on data on pairwise values of angles between drone motion vectors and pairwise values of drone velocities. The hybrid OCM method shows average characteristics for all indicators, which indicates its balance.

The proposed hybrid OCM algorithm, which combines the advantages of PSO and PFM, showed balanced results: the average distance between drones was 14.47 units, which is 45% less than in Boids. The number of collisions decreased to 416 per 1000 simulations, and the energy efficiency improved by 20% compared to Vicsek. A "collision" is understood as the approach of drones to a distance that is less than the set limit in the optimization problem statement.

The algorithms were compared by seven metrics, which showed the advantage of PSO in collision avoidance and high adaptability of PFM to obstacles, while OCM is optimal for scenarios with limited communication. This makes OCM promising for use in limited communication conditions, in particular in agriculture and urban monitoring. Further research will be aimed at the integration of noise-resistant sensors and real-time testing.

Analysis of approaches to the use of a leader in the context of group control showed that the presence of a leader provides advantages in speed of reaction to obstacles, energy efficiency and has disadvantages in scalability and robustness. Movement in a formation simplifies group control, and in some cases reduces energy consumption. Amorphous movement reduces the requirements for communication between drones, since it does not require correction of the movement formation and requires more frequent maneuvers to avoid collisions between drones. The use of data on energy consumption, potential, kinetic energy allows for better prediction of movement to avoid collisions, provides appropriate corrections and does not require complex calculations.

Declaration on Generative AI

During the preparation of this work, the authors used Chat-GPT-4o in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and takes full responsibility for the publication's content.

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