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Comparative analysis of chaotic and deterministic methods to territory coverage by drone swarms

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ABSTRACT

This study proposes a hybrid chaotic-deterministic method for controlling a swarm of unmanned aerial vehicles, integrating social interactions such as separation, cohesion, alignment, and binding with an attraction-driven search strategy. The two-level anti-stagnation system operates at the level of individual agents ('micro') and the collective swarm ('macro') to prevent local minima and maintain controlled trajectory smoothing. The method uses double course conditioning to balance smooth trajectories with stochastic exploration. Meanwhile, an attractiveness function evaluates potential movement directions quantitatively based on territory novelty, distance factors and course stability. Social interaction forces – repulsion, cohesion, alignment and centroid binding – ensure swarm stability and collision avoidance throughout mission execution.

Comparative experimental validation was conducted through multiple simulation launches for each method in irregular polygonal territories. Both the chaotic and deterministic waypoint-based approaches demonstrated exceptional mission reliability, achieving a target coverage threshold in all trials, thereby confirming complete success rates. In terms of coverage efficiency, the chaotic method achieved superior average territory completeness compared to the deterministic approach, representing a measurable improvement. However, this enhanced coverage precision comes at a significant computational time cost: the chaotic method required substantially longer average mission duration compared to the optimized waypoint method. The chaotic approach also exhibited notably higher variability in results, reflecting the inherently stochastic nature of exploration-based methods. Thus, while the chaotic method demonstrates superior coverage efficiency, it exhibits inferior time efficiency compared to the deterministic baseline.

These findings quantify the fundamental trade-off between thorough exploration and time efficiency in unmanned aerial vehicle swarm operations, providing empirical evidence to inform mission-critical deployment decisions. The results suggest that chaotic methods are best suited to scenarios that prioritize comprehensive coverage and adaptability, such as search and rescue operations where undetected casualties would be a critical failure, while deterministic approaches are more effective in time-sensitive missions with predictable environments. The reliability of both methodologies, combined with the quantification of performance differences, enables the selection of methods based on evidence, aligned with specific operational requirements, mission constraints and acceptable risk-time-accuracy trade-off parameters.

Keywords: Information technology; swarm intelligence; chaotic algorithm; multi-agent systems; scan optimization; swarm social interactions; anti-stagnation method; swarm trajectory optimization

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INTRODUCTION

The development of territory scanning technologies has been and remains relevant to this day. In the event of a diverse range of emergencies, including but not limited to floods, earthquakes and wars, there is often a necessity to undertake the search for victims or the assessment of damage. The involvement of human operators in such operations poses a significant risk to their personal safety, as the aforementioned areas are often inaccessible and difficult to reach. The utilization of unmanned aerial vehicles (UAVs) for scanning such areas has been a practice for many years [1], [2].

In light of the substantial consequences that emergencies can entail, the deployment of a group of drones, or a swarm of drones, is frequently employed. The utilization of unmanned aerial vehicle swarms in emergency situations has exhibited substantial practical advantages in a multitude of real-world scenarios, thereby substantiating the imperative for advanced autonomous coordination algorithms.

The 2011 Fukushima nuclear disaster demonstrated the limitations of human intervention in hazardous environments, where radiation exposure prevented direct assessment of reactor damage [3].

Unmanned aerial vehicle (UAV) systems have been demonstrated to provide significant benefits in the realm of aerial reconnaissance, enabling engineers to formulate effective recovery strategies without compromising the safety of human life [4], [5].

However, the initial deployment of UAVs revealed coordination issues when multiple aircraft operated simultaneously in confined airspace, emphasizing the necessity for enhanced collision avoidance and area coverage algorithms [6].

During the 2019-2020 bushfire crisis in Australia, coordinated swarms of UAVs proved essential for monitoring bushfires and searching for victims in smoke-filled areas [7]. Conventional single-UAV operations were plagued by limited coverage and protracted mission durations, while the uncoordinated deployment of multiple UAVs gave rise to excessive scanning and communication interference.

The application of coordinated UAV swarms can be extended to multiple disaster scenarios with varying operational requirements. For example, in urban search and rescue operations following earthquakes, swarm systems must navigate complex three-dimensional environments comprising collapsed structures, unstable rubble and narrow passages, which would impede the operations of individual UAVs. The Fukushima incident further demonstrated the necessity for radiation-resistant autonomous systems that can operate in environments where human presence poses fatal risks. Swarm coordination enables a comprehensive assessment of damage across multiple reactor sites simultaneously [3], [4]. Avalanche rescue operations in mountainous regions present unique temporal and environmental constraints. Buried victims face critical survival windows, so there is a need for rapid area coverage capabilities, which only coordinated swarm systems can provide. This is because the terrain is characterized by unstable snow conditions, limited accessibility and complex human recognition challenges. Maritime rescue operations present further challenges. Swarms must contend with dynamic sea conditions and limited communication range over water. They must also provide rapid area coverage in time-critical scenarios where hypothermia or drowning threatens survival [1], [7].

These operational limitations underscored the critical importance of intelligent swarm coordination algorithms that could optimize coverage while minimizing the risks of overlap and collision [8], [9].

TECHNICAL CHALLENGES IN SEARCH OPERATIONS

Search and rescue operations present distinctive algorithmic challenges that differentiate them from conventional UAV applications [9]. In scenarios where time is of the essence, it is imperative to swiftly cover the area while maintaining adequate resolution to detect casualties. The heterogeneous nature of emergency situations, including urban rubble, forest canopies, and flooded areas, necessitates the development of adaptive motion algorithms capable of adjusting to varying visibility and obstacle density conditions [11].

Contemporary deterministic methodologies, predicated on waypoints, while engendering predictable coverage patterns, frequently prove inadequate for dynamic emergency scenarios, wherein the optimal routes cannot be ascertained in advance. It is evident that obstacles in the environment, areas of no communication, and equipment malfunctions require real-time adaptation capabilities that traditional fixed-route algorithms are incapable of providing [1]. Moreover, the necessity for redundant coverage in critical areas, with a view to averting potential casualties, appears to be at odds with the pursuit of efficiency optimization in deterministic systems.

Energy management constitutes a further critical constraint in emergency operations, wherein UAV swarms must maximize uptime whilst ensuring sufficient battery reserve to return to base. The issue is further exacerbated in heterogeneous swarms comprising diverse drone types, each exhibiting distinct energy profiles, communication ranges, and sensor capabilities [12]. The coordination of such heterogeneous systems necessitates the implementation of sophisticated algorithms that can dynamically balance the objectives of coverage with the constraints of energy across the entire swarm.

Real-world operational limitations encompass multiple technical and environmental constraints that challenge the effectiveness of autonomous swarms. Poor visibility conditions, including smoke, fog, dust and darkness, significantly degrade sensor performance, compromising both obstacle detection and victim identification capabilities [7], [12]. Urban environments introduce dense obstacle fields comprising vertical structures, power lines and debris, necessitating sophisticated three-dimensional collision avoidance systems that go beyond simple waypoint navigation [10]. Terrain complexity further compounds operational challenges: forest canopies obscure ground-level casualties; flooded areas cause GPS signal degradation and communication blackouts; and mountainous regions generate unpredictable wind patterns that affect flight stability [1], [12]. Damage to communication

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infrastructure during disasters creates intermittent connectivity, forcing swarms to operate with degraded coordination or autonomous decision-making capabilities when centralized control becomes unavailable [12]. These real-world constraints highlight the need for adaptive algorithms that can maintain mission effectiveness despite partial system degradation and environmental unpredictability.

The intricacy of contemporary emergency response scenarios necessitates the implementation of UAV swarm algorithms that are capable of performing multiple tasks in a simultaneous manner. These include the comprehensive coverage of the designated territory, collision avoidance, energy optimization, and adaptation to environmental changes in real time. Conventional methodologies predicated on predefined waypoints or elementary rule-based coordination prove inadequate in addressing the dynamic and unpredictable nature of emergency situations [13], [14].

The present study focuses on the chaotic motion algorithm as a promising alternative to deterministic approaches, offering improved adaptability and coverage characteristics in unstructured environments [8]. The algorithm in question draws inspiration from the natural behavior of swarms and chaos theory, thereby providing the requisite flexibility to respond to emergencies while maintaining the coordination necessary for effective multi-agent operations.

The development of such sophisticated algorithms represents a significant advancement in the field of UAV swarm systems, paving the way for the creation of fully autonomous systems capable of independent operation in emergency scenarios. This advancement is crucial in disaster situations where rapid response is imperative for survival, as it has been demonstrated that even a few minutes can make a substantial difference in the outcome.

RELATED WORKS

The application of chaotic dynamics in rotor robotics and unmanned aerial vehicle systems has emerged as a promising paradigm for overcoming the limitations of deterministic algorithms [15]. Conventional approaches rely on predefined trajectories or rule-based coordination. In contrast, chaotic algorithms exploit the characteristics inherent in deterministic chaos, namely aperiodic bounded behavior and extreme sensitivity to initial conditions, in order to create more adaptive and efficient exploration models. This section provides a review of recent developments in chaotic swarm algorithms, analyzing their methodologies, performance characteristics, and relevance to autonomous territory scanning applications.

The primary challenge in the field of swarm robotics pertains to the formulation of exploration strategies for robots with constrained resources that are devoid of advanced sensory, localization, or computational capabilities [16], [17]. Conventional methodologies, predicated on random wandering, while exhibiting computational simplicity, are encumbered by suboptimal parameterization requirements and constrained adaptability to environmental variability. Recent studies have demonstrated that chaotic dynamics and dynamics at the edge of chaos can significantly enhance exploration performance in such minimalistic systems.

Sartorio et al. conducted a study into the use of random Boolean networks (RBNs) as controllers for Kilobot swarms performing target search tasks. RBNs are autonomous systems with discrete states and discrete time, originally developed to model gene regulation processes. These systems are characterized by nodes with Boolean states, which are connected by directed edges. The state of each node is determined by a logical function that acts on the input states of the nodes, thereby creating complex nonlinear dynamics. The study demonstrated that RBNs operating at the edge of chaos – a transitional regime between orderly and chaotic behavior – create research models that outperform traditional Lévy-modulated correlated random walks (LMCRWs).

The experimental methodology employed realistic simulations of Kilobot platforms, incorporating individual variability in course deviation and movement characteristics. This heterogeneity, which is often considered problematic in swarm systems, was explicitly exploited as a useful feature rather than an artefact to be corrected. The RBN of each robot was employed to regulate the turn angles and step lengths of the robots by extracting binary state templates from the network and converting them into motion parameters. The network evolved autonomously according to synchronous update rules, and the resulting dynamics determined the robot's exploration trajectory.

The performance evaluation was centered on the average first-pass time, defined as the duration for a robot to locate a randomly positioned target within a confined circular arena. The findings demonstrated that RBNs with suitable network sizes (notably, N = 20 nodes) attained a search time of approximately 1300 seconds, in comparison to 988 seconds for the optimally parameterized LMCRW baseline. However, the critical conclusion was not only the equivalence of performance, but also the relationship between network dynamics and exploration efficiency.

Quantitative analysis of chaotic properties employed sensitivity to initial conditions as the primary metric. The dynamic regime of each controller was characterized by the introduction of small perturbations to network states and the subsequent measurement of the evolution of Hamming distances over time. Networks that exhibited positive sensitivity values demonstrated divergence of perturbed trajectories, indicating chaotic dynamics or dynamics on the edge of chaos. Correlation analysis revealed a strong negative correlation between sensitivity to perturbations and first-pass time for networks with corresponding size constraints. This suggests that higher chaotic sensitivity corresponds to more efficient exploration.

Subsequent refinement using evolutionary robotics techniques resulted in the development of evolutionary Boolean networks (EBNs), which retained chaotic dynamics while optimizing connection patterns and logical functions. A genetic algorithm incorporating a tournament selection, simulated binary crossover and polynomial mutation was utilized to evolve populations of 40 networks over 700 generations. The optimal EBN configuration attained a first-pass duration of 913 seconds, representing a 7.6 % enhancement over LMCRW, while preserving dynamics on the periphery of chaos, characterized by Δ values ranging from 0.2 to 0.4. This finding indicates that evolutionary optimization does not necessitate the compromise of advantageous chaotic properties to attain performance enhancements.

Network activation patterns within the study were analyzed, revealing different modes of behavior. It was observed that networks with excessive step length ranges ($N \geq 28$) generated trajectories that exceeded the size of the arena, resulting in frequent collisions with walls and degraded performance. This limitation was addressed by evolution, which directed such networks towards ordered modes (low Δ values) that maintained smaller, more controllable step lengths. Conversely, networks of an appropriate size ($N = 20$-22) enabled evolution to exploit chaotic dynamics fully, as maximum stride lengths remained commensurate with the scale of the environment [18].

Whilst the focus of RBN-based approaches is on minimalist local control, bio-inspired metaheuristic algorithms offer additional opportunities for global trajectory optimization in complex environments [19]. The present study investigates the application of particle swarm optimization (PSO), a technique inspired by the collective behavior of flocks of birds, in the planning of the trajectory of UAVs. However, classical PSO implementations are susceptible to premature convergence to local optima, slow convergence rates, and sensitivity to parameter settings. These constraints are particularly pronounced in high-dimensional optimization problems with constraints [20].

Chu et al. developed the Improved Chaotic-VAINDIWPSO (IC-VAINDIWPSO) algorithm, which integrates chaos theory into several components of the PSO structure with a view to overcoming the shortcomings identified in the existing literature. This approach was tested on three-dimensional trajectory planning for an unmanned aerial vehicle in complex terrain with multiple cylindrical threat zones, requiring simultaneous optimization of trajectory length, threat avoidance, altitude constraints, and trajectory smoothness. The algorithm introduces three main innovations.

Firstly, improved nonlinear dynamic inertial weights (INDIW) replace the standard linear decay strategy.

Secondly, adaptive velocity control alters the behavior of particle updates in accordance with fitness evolution. In the event of an improvement in a particle’s fitness between successive iterations, its velocity is updated in accordance with standard PSO equations, thus enabling it to continue moving in the direction of promising regions. Conversely, when fitness deteriorates, the particle retains its previous velocity, thereby preventing counterproductive changes in direction.

Thirdly, chaotic initialization employs logistic maps to generate uniformly distributed initial populations, as opposed to purely random initialization. The initialization process involves the generation of 1,000 candidate particles, the evaluation of their fitness, and the selection of the 500 most fit individuals as the initial population. This approach provides a more extensive overview of the solution space and reduces initialization bias towards suboptimal regions.

Furthermore, during the course of evolution, when the rate of fitness change (FCR) falls below a certain threshold and less than two-thirds of the maximum number of iterations have elapsed, the global best particle undergoes a chaotic mutation.

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This mechanism employs the ergodic properties of chaos theory to circumvent local optima, thereby progressively enhancing the search as it approaches convergence.

The experimental validation employed a digital terrain model of Christmas Island, Australia, with Unmanned Aircraft Vehicle missions necessitating navigation from initial to final coordinates, circumventing cylindrical threat zones with predetermined radii and safety margins. The cost function integrated path length, penalties for proximity to threats, altitude violations, and smoothness metrics based on turn and climb angles.

A comparative analysis with the standard PSO and an intermediate variant of VAINDIWPSO (including only INDIW and speed disturbances) revealed a significant improvement in performance. In the seven-threat scenario, IC-VAINDIWPSO achieved average fitness values of 5575.78, in comparison to 7350.46 for PSO and 6704.68 for VAINDIWPSO. Convergence occurred in 20 iterations for the present study, in comparison to 449 for PSO and 250 for VAINDIWPSO, representing a reduction in the number of iterations by 95.5 % and 92 %, respectively. The initialization time was reduced to 0.644 seconds, which is 86.35 % faster than the 4.745 seconds required by PSO.

A scalability analysis was conducted in environments with varying threat densities (1-7 obstacles), which demonstrated that the advantages of IC-VAINDIWPSO become more pronounced as the complexity of the environment increases. In scenarios involving three threats, all algorithms demonstrated a capacity to achieve near-optimal solutions. However, with five threats, the average fitness of IC-VAINDIWPSO, which was 5229.18, significantly outperformed PSO, which was 6058.12. Further reliability testing was conducted on ten random threat configurations, the results of which confirmed a stable advantage in both fitness and convergence speed values.

A visual analysis of the generated trajectories demonstrated that IC-VAINDIWPSO generates smoother, flyable trajectories that maintain an appropriate flight altitude above the terrain, thereby effectively avoiding threat zones. In contrast, PSO trajectories exhibited uneven turn angles and suboptimal altitude profiles, indicating local optima entrapment [22].

COMPARATIVE CONTEXT AND ALGORITHMIC DIFFERENCES

RBN-based methods operate at the level of individual agents without global coordination (suitable for limited resources), while chaotic PSO operates at the population level for pre-flight mission planning. RBNs leverage dynamics at the edge of chaos to derive direct benefits from exploration, while chaotic PSO employs chaos to circumvent local optima. It is evident that none of the studies under review have considered heterogeneous swarms, which represent a pivotal aspect of the proposed algorithm. These findings serve to corroborate the efficacy of chaos theory. RBNs correspond to optimally tuned baselines, and chaotic PSO reduced iterations by more than 95 %. The hypothesis of evolutionary optimization with chaos preservation suggests that automatic design methods have the capacity to discover effective controllers for complex swarm tasks.

PROBLEM STATEMENT

The primary objective of this study is to develop a hybrid chaotic-deterministic method for autonomous coverage of a territory by a swarm of UAVs. This approach is informed by an analysis of existing approaches and an identification of the limitations of deterministic methods in emergency response scenarios. The proposed method aims to address the fundamental trade-off between the thoroughness of reconnaissance and the time of mission execution.

The method builds upon a previously established multi-level control architecture [9], [12] that integrates social interaction forces (repulsion, cohesion, alignment, centroid binding) with chaotic exploration mechanisms. This architectural foundation ensures both swarm stability and adaptive coverage behavior in irregular polygonal territories, providing the structural basis for the following specific research objectives.

The specific research objectives are formulated as follows.

1. Design a multi-criteria direction selection function that incorporates unscanned area bias, heading continuity and social force integration. Formulate an attractiveness function for directional decision-making that can quantitatively evaluate candidate movement directions during chaotic exploration.

This function should integrate the following:

– territory novelty assessment through counting unscanned cells within directional sampling cones;

– heading preference weighting to favor continuation of the current trajectory and minimize turn energy;

– distance-decay factors to evaluate target reachability;

– social force contributions from separation, cohesion and alignment with neighboring agents.

This multi-objective function should enable rational exploration under chaotic conditions, favoring direction selection towards unexplored areas while maintaining swarm cohesion and energy-efficient trajectories.

2. Development of a two-level anti-stagnation system that integrates micro-level agent escape mechanisms and macro-level swarm redirection. A level-layer anti-stagnation architecture must be implemented to prevent confinement to local minimums during chaotic exploration. At the micro level, individual agents require stuck detection at a per-drone level, based on scan cell revisitation patterns. This triggers autonomous escape maneuvers towards distant, unscanned targets. At the macro level, the system must be able to detect when a critical proportion of agents are operating within already-scanned areas and initiate coordinated redirection towards a shared global target in unexplored territory. The system must maintain the stochastic characteristics of chaotic movement while ensuring progressive area coverage through individual initiative and collective coordination mechanisms.

3. Implementing double-course conditioning mechanism. A double-course conditioning mechanism must be established to balance randomness in exploration with stability in movement. This involves implementing exponential moving average (EMA) filtering of desired heading angles at the agent level and applying bounded turn rate constraints to prevent excessive angular acceleration. The smoothing parameters must be calibrated to minimize oscillatory behavior and energy consumption resulting from rapid direction changes, while ensuring sufficient stochastic variability for thorough territory exploration. The system should incorporate self-propulsion adjustment to maintain normal speed targets and minimize unnecessary velocity fluctuations during chaotic scanning operations.

4. A rigorous comparative experiment must be conducted to quantify the differences in performance between chaotic and deterministic (waypoint-based) approaches, measuring coverage efficiency, temporal performance, result stability and mission reliability.

5. The experimental protocol should employ multiple simulation runs ($n \geq 10$) for each method and measure the following:

– the percentage of coverage achieved within fixed time intervals;

– the time taken to reach target coverage thresholds (≥ 95 %);

– the coefficient of variation in completion times across replications to assess result stability;

– the mission success rate under heterogeneous swarm conditions with agent loss scenarios.

Statistical analysis should include mean values, standard deviations, confidence intervals and significance testing in order to provide empirical evidence of the performance characteristics of the methods.

6. A quantitative analysis of the relationship between coverage and time in chaotic versus deterministic scanning methodologies is required to inform mission planning decisions. This analysis must systematically evaluate the inherent trade-off between coverage thoroughness and mission duration.

The analysis should quantify the following:

– coverage efficiency curves showing the area scanned as a function of elapsed time for both approaches;

– redundancy metrics measuring overlap and re-scanning frequency;

– energy consumption profiles relative to coverage achieved;

– adaptive behavior in response to dynamic environmental changes or agent failures.

This empirical evidence will inform the selection of methods for specific scenarios, determining when thoroughness-prioritized chaotic exploration outweighs time-critical deterministic path-following, particularly in emergency response applications where either rapid reconnaissance or comprehensive damage assessment may be paramount.

The study is constrained to two-dimensional scanning of the territory in a simulation environment, with a focus on the algorithmic and coordination aspects of swarm behavior.

CHAOTIC-DETERMINISTIC METHOD

The proposed chaotic method of controlling a swarm of drones can be described as follows:

1) local agent behavior:

– each drone maintains an individual map of the territory, tracking scanned and unscanned areas;

– movement directions are determined by an attractiveness function that evaluates potential angles based on territory novelty, distance factors and course stability;

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– direction selection combines deterministic prioritization of promising areas with controlled randomness, choosing from the highest-ranked candidate directions;

2) micro-level anti-stagnation:

– individual drones continuously track their movement over recent time steps;

– when movement falls below an efficiency threshold, adaptive angular correction is automatically activated;

– stochastic rotation allows escape from local traps by applying random directional perturbations;

– this mechanism prevents the immobilization of individual agents in confined or already explored areas;

3) social interaction forces:

– the repulsion force prevents collisions by pushing drones away when they approach a critical distance;

– the cohesion force attracts agents to local neighboring centroids, maintaining the structural integrity of the group;

– alignment synchronizes speeds within local groups, reducing chaotic trajectory fluctuations;

– centroid binding connects agents to the global center of the swarm, preventing excessive dispersion and fragmentation;

– these forces combine into a single social vector that ensures swarm stability and prevents collisions;

4) anti-stagnation at the macro level:

– the global swarm stagnation coefficient continuously monitors the collective efficiency of all agents;

– when this coefficient exceeds a threshold that indicates widespread stagnation, global redirection is activated;

– the system then forms a common area vector that directs the entire swarm towards unexplored areas, thereby preventing collective traps in which most agents remain confined to areas that have already been scanned;

5) double-course conditioning:

– first-level inertia smoothing acts as a low-pass filter, dampening sudden directional changes through weighted averaging of previous and new angles;

– second-level adaptive stabilization aligns individual movement with the average orientation of local neighbors;

– this two-level filtering provides smooth, energy-efficient trajectories while preserving the stochastic variability necessary for effective exploration;

6) combined stabilized control:

– the method hierarchically prioritizes goals: global reorientation has the highest priority, followed by individual escape protocols and then normal exploration;

– the desired direction passes through a double conditioning filter before physical execution;

– the final motion vector integrates exploration goals, social constraints and stability requirements;

– the system maintains a balance between chaotic exploration and coordinated swarm behavior throughout the mission.

This sequence provides adaptive dispersion, coordinated congestion resolution and controlled trajectory randomness, effectively combining exploration of new areas with the use of accumulated coverage information.

SOCIAL INTERACTION IN A SWARM

Social interaction between agents constitutes a fundamental component of the proposed chaotic method, thereby ensuring swarm stability, collision avoidance, and coordinated movement. The model is predicated on the principles of Swarm Chemistry, whereby the behavior of each drone is formed as a result of the superposition of several interaction vectors, namely repulsion, cohesion, alignment, and binding to the group's centroid. These forces provide a balance between individual autonomy and collective coordination.

The repulsion force $\overrightarrow{F_{repulsion}}$ is initiated when the drones approach a critical distance from each other, thereby preventing collisions. This is calculated as a vector directed away from neighboring agents, with a force that decreases proportionally to the square of the distance between them:

$$\overrightarrow{F_{repulsion,i}} = \sum_{j \in N_i} k_r \frac{\overrightarrow{p_i} - \overrightarrow{p_j}}{|\overrightarrow{p_i} - \overrightarrow{p_j}|^2 + \epsilon},$$

where N_i is set of i-th drone neighbors; k_r is coefficient of repulsion; ϵ is small stabilizing parameter to avoid division by 0; $\overrightarrow{p_i}$ is position vector (coordinates) of the current drone i (the drone for which the repulsive force is currently being calculated); $\overrightarrow{p_j}$ position vector (coordinates) of neighboring drone j (the drone that creates the repulsive effect).

Cohesion, in turn, plays a pivotal role in maintaining the structural integrity of the system. This component is responsible for ensuring the cohesion of the drone population within the group, thereby preventing excessive dispersion and fragmentation of the swarm. The cohesion vector $\overrightarrow{F_{cohesion,i}}$ is defined as an attractive force directed towards the average position (centroid) of the nearest neighbors:

$$\overrightarrow{F_{cohesion,i}} = k_c\left(p_{avg,i} - \overrightarrow{p_i}\right),$$

where k_c is cohesion coefficient, which regulates the force of attraction; a $p_{avg,i}$ is the average position of neighbors, calculated as:

$$p_{avg,i} = \frac{1}{|N_i|}\sum_{j\in N_i}\overrightarrow{p_j}.$$

This mechanism ensures that individual agents do not deviate excessively from their local group, thereby preserving the requisite local cohesion of the swarm.

The subsequent critical vector is alignment, which ensures that the movement of drones within a local group is coordinated. This synchronization of trajectories has been shown to significantly contribute to the stability of the swarm as a whole dynamic system, thereby minimizing chaotic fluctuations in the trajectories of individual agents.

The alignment force directs the agent toward the average velocity vector of its neighbors:

$$\overrightarrow{F_{align,i}} = k_a\left(\overrightarrow{v_{avg,i}} - \overrightarrow{v_i}\right),$$

where k_a is equalization factor, $\overrightarrow{v_i}$ is velocity vector of the current *i*-th drone and $\overrightarrow{v_{avg,i}}$ is the average velocity vector of neighbors, defined as:

$$\overrightarrow{v_{avg,i}} = \frac{1}{|N_i|}\sum\nolimits_{j\in N_i}\overrightarrow{v_j},$$

where $\overrightarrow{v_j}$ is this is the velocity vector of the neighbouring drone j.

This enables drones to synchronize their movement directions, ensuring smooth transitions between zones and effectively avoiding collisions caused by unsynchronized movement.

In order to impede both excessive expansion and fragmentation of the swarm at the global level, an additional vector is introduced. This vector is a link to the centroid ($\overrightarrow{F_{centroid}}$). This force binds agents to the global center of mass (centroid) of the entire system, ensuring macroscopic cohesion:

$$\overrightarrow{F_{centroid,i}} = k_g\left(\overrightarrow{p_{centroid}} - \overrightarrow{p_i}\right),$$

where k_g is centripetal force and $p_{centroid}$ is coordinates of the swarm center, calculated as:

$$\overrightarrow{p_{centroid}} = \frac{1}{N}\sum_{i=1}^{N}\overrightarrow{p_i},$$

where N is total number of drones. This component is critical for maintaining swarm integrity even under conditions of asymmetric agent distribution or global redirection maneuvers.

All of the above components of social interaction – repulsion ($\overrightarrow{F_{repulsion}}$), cohesion ($\overrightarrow{F_{cohesion}}$), alignment ($\overrightarrow{F_{align}}$) and binding to the centroid ($\overrightarrow{F_{centroid}}$) – integrate into a single aggregate vector of social power:

$$\overrightarrow{F_{social,i}} = \overrightarrow{F_{repulsion,i}} + \overrightarrow{F_{cohesion,i}} + \overrightarrow{F_{align,\,i}} + \overrightarrow{F_{centroid,i}}.$$

This resulting vector $\overrightarrow{F_{social,i}}$ serves as the basis for calculating the final direction of the drone's movement.

MULTI-CRITERIA DIRECTION SELECTION

Local behavior constitutes the foundation for each drone's unique dynamics, thereby ensuring the flexibility and stability of the swarm in its entirety. At this level, each agent possesses a map of the territory, including information regarding scanned and unscanned areas. Concurrently, data pertaining to its own status contributes to the decision-making process.

The fundamental objective is to harmonize adherence to social norms with one's personal aspirations, namely, the exploration of uncharted territory. The drone's navigation strategy entails the pursuit of areas that have not been previously scanned, while concurrently evading excessive regularity, a tactic that facilitates more equitable coverage of the territory.

In order to implement local exploration, it is necessary for the drone to possess a mechanism that enables it to select its direction of movement not only randomly, but also taking into account the value of specific areas for exploration. In essence, even in situations involving chaotic movement, a discernible "rationality" emerges. The agent exhibits a propensity to maneuver towards areas where it can maximally contribute to the coverage of the territory, while eschewing superfluous alterations in course and the repetition of scanning the same regions.

For this purpose, the attractiveness function $S(a)$ is calculated for each possible deflection angle α:

$$S(a) = E(a)\cdot\left(1 + \gamma D(a)\right)\cdot H(a),$$

where $E(a)$ is assessment of the potential novelty of the area, taking into account the number of unscanned cells in the selected direction; $D(a)$ is the distance factor to the target, which encourages the drone to move to more remote areas and prevents excessive concentration of agents within already explored boundaries; $H(a)$ is a bonus of stability, which reduces the likelihood of sudden changes in direction and makes the trajectory smoother; γ is weight coefficient that determines the significance of the distance factor.

Following the calculation of $S(a)$ values for all candidates, the direction is selected at random from the top 80 % of options. This decision enables the synthesis of a deterministic emphasis on innovation with an element of randomness.

Consequently, the drone does not invariably select the optimal direction in the strict sense, but rather generates a movement that is adequately directed to circumvent superfluous repetitions, while simultaneously being sufficiently random to avert the consequences of symmetry and mass accumulation.

The direction that proves successful is denoted by a vector $\widehat{d_{explore,\imath}}$. The formation of the agent's local movement vector $\overrightarrow{V_{local,\imath}}$ entails the integration of individual objectives (i.e., exploration) and collective constraints (i.e., social forces):

$$\overrightarrow{V_{local,\imath}} = \beta \cdot \widehat{d_{explore,\imath}} + (1 - \beta) \cdot \widehat{F_{social,\imath}},$$

where $\widehat{d_{explore,\imath}}$ is normalized local exploration vector; $\widehat{F_{social,\imath}}$ is normalized total vector of social power; $\beta \epsilon [0, 1]$ is the balance between individual exploration and social harmony.

The vector described above $\overrightarrow{V_{local,\imath}}$ defines the basic movement of the drone in normal mode. However, to avoid "local minima", there are exception mechanisms that can temporarily override this movement. They operate on two levels.

ANTI-STAGNATION MECHANISMS OF AGENTS

The fundamental compromise between exploration and exploitation is central to the execution of autonomous environment exploration tasks utilizing swarm complexes. The employment of controlled chaotic motion facilitates the maximization of territory coverage, a consequence of the stochastic nature of trajectories. However, this approach gives rise to the issue of local minima, or "local minima". Agents may become entrapped within configuration spaces, such as already explored areas, ravines, and enclosed spaces. In these environments, their chaotic movement does not result in the discovery of new areas; rather, it leads only to the repetition of scanning already known areas.

One proposed solution to this problem is the implementation of a two-level anti-stagnation system that functions at the level of individual agents (micro level) and at the level of the entire swarm (macro level). This approach would generate a synthetic effect and ensure the robustness of the system.

To circumvent stagnation at the micro level, each agent is endowed with the capacity for self-diagnosis of its own effectiveness. The basis of this mechanism, termed per-drone stuck-detection, is continuous monitoring of the dynamics of its own movement.

To quantitatively assess movement performance, the drone's position changes over the last T_s steps are recorded and the relative displacement $\Delta p(t)$is calculated:

$$\Delta p(t) = \frac{1}{T_s} \sum_{i=1}^{T_s} |p(t - i) - p(t - i - 1)|,$$

where: $p(t)$ is drone coordinates at a given moment in time t; T_s is depth of the time horizon of the analysis.

If $\Delta p(t) < \epsilon_s$, where ϵ_s is the minimum change for classifying movement as effective, quantified as the number of unique grid cells visited by the agent (set to 4 cells). If this condition is met, the agent is considered "stuck" and activates the adaptive angular correction mechanism:

$$a_{new} = a_{current} + \theta_s \cdot R(-1{,}1),$$

where a_{new} is the resulting angle of movement that the drone will take in the next step to exit the state of stagnation; $a_{current}$ is the angle at which the drone was moving until the protocol was activated; θ_s is maximum turning angle for escaping the trap; $R(-1{,}1)$ is random value within the range $[-1{,}1]$.

This mechanism enables the drone to adaptively adjust its trajectory, thereby reducing the probability of becoming immobilized while preserving a state of controlled chaos. It is also noteworthy that the system does not entirely discard prior experience when utilizing the current direction angle; rather, it makes corrections to it.

The primary benefit of this approach is the rejection of deterministic maneuvers. Should the system invariably respond to stagnation in a uniform manner, there would be a risk of falling into yet another, more complex cyclical trap. The incorporation of a stochastic factor $R(-1{,}1)$ ensures that each attempt to escape the trap is unique.

Consequently, rather than executing the same command in a mechanistic manner, the drone engages in a process of improvisation, thereby significantly enhancing its probability of identifying a trajectory that leads to previously unexplored territory.

Therefore, when the drone detects individual stagnation ($\Delta p(t) < \epsilon(s)$), its desired direction a_{new} is generated randomly, disregarding the base vector $\overrightarrow{V_{local,\,i}}$ at that particular moment. This novel approach subsequently becomes the prevailing direction of movement.

At the swarm level, a macro anti-stagnation strategy is implemented, which is initiated when the majority of agents remain in already scanned areas. At this level, the overall state of the swarm is analyzed by introducing an integral indicator, the swarm stagnation coefficient (J).

This coefficient is a quantitative metric of the "health" of the entire system and is calculated using the following formula:

$$J = \frac{1}{N}\sum_{i=1}^{N} 1_{\{\Delta p_i < \epsilon_s\}},$$

where N is the number of drones in the swarm; $1_{\{\Delta p_i < \epsilon_s\}}$ is stagnation indicator (1 if the drone is stationary, 0 otherwise); ϵ_s is stagnation sensitivity threshold (or minimum effective displacement threshold).

If $J > J_{th}$, where J_{th} is the threshold value, this signals that local efforts are insufficient and the swarm needs global coordination.

In this case, a global redirection vector ($\overrightarrow{V_{global}}$) is formed for the swarm:

$$\overrightarrow{V_{global}} = \sum_{i=1}^{N} w_i \; d_i,$$

where d_i is direction to the nearest unscanned areas for the i-th drone; w_i is weight coefficient, which depends on the local "novelty" of the territory.

The final step is to integrate both control levels into a single hybrid model. The motion vector of the i-th drone is defined as the weighted sum of its local motion vector $\overrightarrow{V_{local,\,i}}$ and the global swarm redirection vector ($\overrightarrow{V_{global}}$):

$$\overrightarrow{V_{final,i}} = \alpha\overrightarrow{V_{local,\,i}} + (1-\alpha)\overrightarrow{V_{global}},$$

where $\alpha \in [0,1]$ is a coefficient that determines the balance between local exploration and global redirection.

Upon activation of the global mechanism, the desired direction a_{new} is strictly derived from the resulting hybrid vector $\overrightarrow{V_{final,i}}$. This vector possesses the highest priority within the decision-making hierarchy, effectively overriding and suppressing both the baseline local movement vector $\overrightarrow{V_{local,i}}$ and any stochastic correction angles a_{new}. generated by individual anti-jamming protocols. By enforcing such a centralized redirection, the system ensures that the collective behavior temporarily supersedes individual autonomy to resolve critical deadlocks.

This hierarchical approach is specifically designed to address the challenges posed by simultaneous individual and collective stagnation, thereby facilitating the continuous expansion of the explored territory and ensuring the optimal distribution of computational and energetic resources within the multi-agent system.

DOUBLE COURSE CONDITIONING AND STABILIZATION

Double course conditioning represents a pivotal element of the swarm stabilization system, aiming to maintain a balance between the inherently chaotic nature of local exploration and the requisite smoothness of drone trajectories. In the course of exploring the territory, each agent perpetually adjusts its direction of movement in response to local factors (randomness, social forces, obstacles). These factors can result in variations in course, substantial turbulence, and energy dissipation. In order to circumvent the aforementioned effects, the proposed method implements a two-tiered conditioning system that incorporates inertial smoothing and adaptive stabilization.

In the initial phase of stabilization, the current direction of movement is smoothed using a first-order filter. This filter is designed to simulate the effect of inertia.

The new course angle a_t is determined as the weighted sum of the previous angle a_{t-1} and the new desired direction a_{new}:

$$a_t \;=\; \lambda a_{t-1} \;+\; (1-\lambda)a_{new},$$

where a_{t-1} is angle of movement in the previous step; a_{new} is desired direction (angle) obtained at the previous stage, i.e., the angle from $\overrightarrow{V_{local,\,i}}$, $\overrightarrow{V_{final,i}}$ or the correction $\mathrm{a_{new}}$; $\lambda \in [0,1]$ is inertial smoothing coefficient.

The value λ determines the degree of "memory" of the drone. Primary conditioning acts as a low-frequency filter that dampens sudden changes in direction.

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The second level of stabilization incorporates not only its own previous course but also the average orientation of the local environment. The drone adjusts its direction in accordance with the collective movement of its neighbors, thereby reducing chaotic fluctuations within the microgroup.

Adaptive stabilization can be expressed as follows:

$$a_t = a_{t-1} + \mu(\overline{a_{N_i}} - a_t),$$

where a_{N_i} is average direction of movement (average angle) of neighbors of drone i; $\mu \in [0, 1]$ is stabilization coefficient.

The parameter μ regulates the degree of influence of social orientation. Adaptive stabilization provides dynamic alignment of directions within a local group.

Double conditioning reduces the dispersion of direction angles within a group of drones without reducing it to zero, which preserves the necessary level of stochasticity.

Formally, if we denote the root mean square deviation of directions as σ_a^2, then the following is true:

$$\sigma_a^2 = (1 - \lambda - \mu)\, \sigma_a^2,$$

where reduced σ_a^2 means stabilization, but not complete synchronization. The method maintains a balance between stability of movement and chaotic variability necessary for effective exploration.

It is important to note that adaptive stabilization and alignment do not duplicate each other. Alignment is a vector force that influences the choice of the desired direction (it is part of $\overrightarrow{F_{social,i}}$). Stabilization is a scalar filter that smooths the selected angle, a_t, to make the movement more coherent and physically smoother. Alignment and stabilisation operate at different stages of the computational process: alignment influences the initial direction selection, while stabilisation refines the final angular output.

COMBINED STABILIZED CONTROL

Combined stabilized control represents the culminating stage of the drone's computational cycle, wherein all previously delineated mechanisms comprising social forces, local exploration, anti-stagnation protocols, and conditioning are integrated into a unified, physically executable movement (Fig. 1).

The decision-making process is characterized by a clear prioritization of objectives. At each step, the method first determines the "desired direction" (a_{new}) based on the current state of the agent. In the event that the swarm is in a state of global stagnation ($J > J_{th}$), the desired direction is calculated from the hybrid vector $\overrightarrow{V_{final,i}}$, which has the highest priority. In the event that only individual stagnation is active ($\Delta p(t) < \epsilon(s),$) the desired direction a_{new} is generated on a stochastic basis to facilitate the process of escaping the trap. In all other ordinary cases, the desired direction a_{new} is calculated from the base vector $\overrightarrow{V_{local,i}}$. This vector combines individual exploration and total social force.

The resulting desired direction a_{new}, irrespective of its provenance, is not implemented immediately. Conversely, the information is transmitted to the input of the "Double Conditioning" system, which functions as a final filter to ensure smooth and coherent movement. Initially, the angle undergoes inertial smoothing (first-order filter), which prevents sharp fluctuations, according to the formula:

$$a_t = \lambda a_{t-1} + (1 - \lambda) a_{new}.$$

Then, the smoothed angle a_t is further adjusted relative to the average direction of neighbors (a_{N_i}), which enhances the local consistency of the swarm:

$$a_t = a_t + \mu(\overline{a_{N_i}} - a_{t-1}).$$

The final adjusted angle constitutes the drone's final target direction. The subsequent physical movement of the agent is executed in the aforementioned direction, contingent upon genuine physical limitations such as maximum turning velocity and responsive control accuracy. The method is designed to maintain a stable equilibrium by preserving the chaotic variability necessary for effective exploration while ensuring that movement remains smooth, stable, and fully consistent with the coordinated actions of neighboring agents.

COMPUTATIONAL COMPLEXITY

Understanding the computational complexity of swarm algorithms is crucial for assessing their scalability in larger deployments. In the case of the chaotic method, the most computationally expensive operation at each time step is neighbor detection, whereby each drone scans all n agents to identify those within communication range. This results in $O(n)$ complexity per agent. Social force calculations are then repeated for k neighbours, resulting in $O(k)$ operations where $k \leq n$. Direction selection using the attraction function selects a fixed number of candidates (typically 10), resulting in constant complexity of $O(1)$. Periodic scanning of the grid for unscanned areas requires $O(W \times H)$ operations

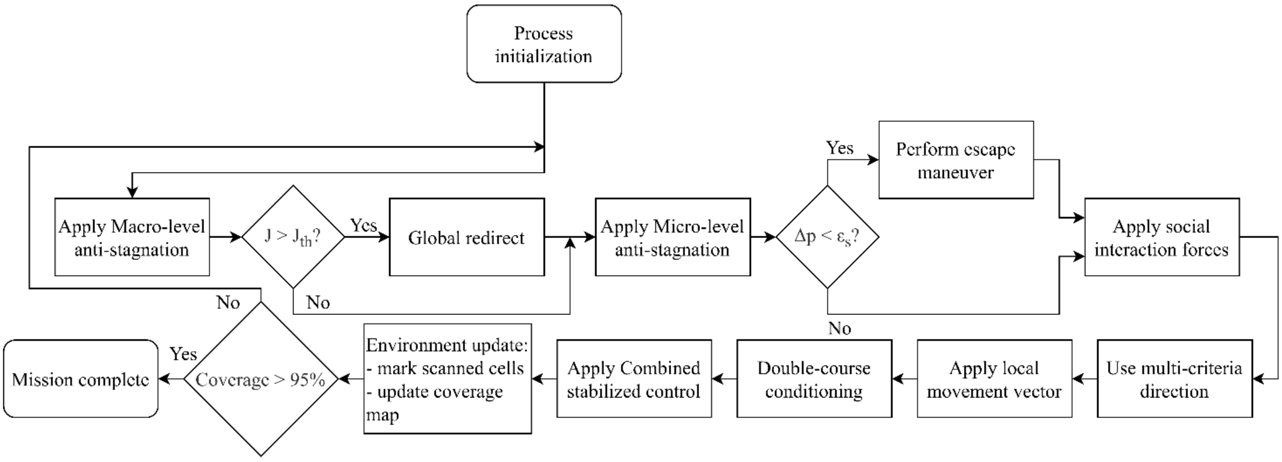

Fig. 1. **Flowchart of the Chaotic-Deterministic swarm movement method**
***Source*: compiled by the authors**

and is performed at 1.5-second intervals. Summing these components, the complexity per step for a single drone is $O(n)$ and for the entire swarm it is $O(n^2)$, since each of the n drones perform $O(n)$ operations. Over the course of a mission requiring S time steps (approximately 351 iterations in 35.13 seconds), the total complexity is $O(n^2 \times S)$. The deterministic method exhibits similar $O(n^2)$ complexity, but with reduced constant factors.

Thus, both methods scale quadratically with swarm size due to pairwise neighbor detection. However, spatial indexing structures (k-d trees and grid-based hashing) can reduce neighbor detection to $O(n\,log\,n)$ or $O(n)$, enabling scalability to hundreds of agents.

For moderate-sized swarms (n ≤ 50), trajectory optimization is the most effective way to improve efficiency. As the size of the swarm increases, the quadratic increase in complexity requires the algorithms to be optimized, specifically by using spatial indexing for neighbor detection and boundary-based tracking to replace $O(W \times H)$ grid scanning. This is necessary in order to maintain real-time performance when deploying more than 50-100 agents.

EXPERIMENTS

A series of computational simulations were conducted for the purpose of validating and empirically evaluating the performance of the proposed chaotic method. The implementation of all calculations, modeling, and analysis of results was conducted using the Python 3.13.7 programming language. Essential core libraries, such as numpy for numerical array operations and shapely for handling polygonal boundaries and spatial analysis, were utilized. The simulation was containerized using a Docker environment.

The model was implemented on a territory defined as a complex irregular polygon, which simulates realistic conditions with uneven boundaries. The specific scan area boundary was defined by an irregular 5-vertex contour. The simulation space was discretized into a grid of 34×23 cells (782 total cells), with the grid cell size set to 20 units.

Specific thresholds were implemented to govern the anti-stagnation and movement control mechanisms. For classifying local stagnation, the drone was considered stuck if it visited no more than 3 unique cells. The escape protocol was triggered only after 3 consecutive detections. Furthermore, the maximum turn rate was constrained to per step, and a minimum turn threshold of was enforced to stabilize the movement.

In consideration of the high sensitivity exhibited by chaotic systems to initial conditions and control parameters (Table 1), a preliminary optimization stage was initiated prior to conducting the primary experiments. The objective of this stage was to automatically determine the optimal set of hyperparameters that provides the best balance between speed and coverage quality. This process is an iterative pipeline that repeatedly executes a full simulation cycle. Subsequent to each iteration, the “fitness” of the configuration is appraised. According to the findings of this evaluation, stochastic mutations are applied to the parameters, and the process is repeated.

The key coefficients governing the three main aspects of swarm behavior were optimized:

1) social interactions: cohesion strength and alignment strength;

Table 1. **Parameters and their range**

Parameter	Range	Sensitivity
k_c	[0.5, 10.0]	Very high
k_g	[0.2, 5.0]	High
k_a	[0.0, 3.0]	Average
J_{th}	[0.1, 0.9]	High
θ_s	[5.0, 90.0]	High
λ	[0.1, 1.0]	Average
μ	[0.1, 1.0]	High
H_α	[0.0, 0.5]	Low
ϵ_s	[1.0, 10.0]	High

Source: Compiled by authors

2) the exploration aggressiveness is determined by the priority coefficient of unexplored areas;

3) the concept of anti-stagnation sensitivity pertains to the thresholds that determine the activation of both individual and global escape mechanisms.

A scan was considered successful if it achieved a coverage level of at least 95 %. Following the optimization phase, the optimal set of hyperparameters was documented and used to run the main simulations.

The final coefficient values obtained from this convergence process reflect the adaptation of swarm kinematics to the polygon topology. Specifically, to ensure a balance between maneuverability and trajectory smoothness, the inertial smoothing and adaptive stabilization coefficients were fixed at $\lambda = 0.4$ and $\mu = 0.3$, respectively. This allows the system to act as a low-pass filter, cutting off stochastic decision "noise", while the maximum turn angle θ_s was limited to 30° to prevent oscillations.

Regarding the anti-stagnation settings, the individual stagnation threshold (ϵ_s) was defined at 4 unique cells, minimizing false positives during dense maneuvering. The global threshold J_{th} was set at 0.45, activating collective redirect only when nearly half the swarm becomes unproductive. The critical balance between exploration and integrity was achieved by setting a high priority for unexplored zones (2.03), compensated by enhanced cohesion ($k_c = 3.5$), which prevents group fragmentation during rapid expansion.

Each experimental trial began with the swarm selecting a random initial trajectory to ensure unbiased starting conditions. During mission execution, the swarm navigated the territory autonomously, systematically covering designated areas. Once the coverage level in the current area reached the set threshold, the swarm proceeded to the nearest unscanned area. To assess relative effectiveness and establish performance benchmarks, the results of the chaotic approach were compared with those of an alternative, deterministic method: Waypoint Collision Avoidance [8].

RESULTS

During the experiment, 20 simulation launches were performed for each method. The two approaches exhibited a high degree of reliability, attaining a target coverage rate of ≥ 95 % in all cases. It is noteworthy that no catastrophic failures were recorded, thereby validating the efficacy of both approaches for critical missions.

The primary distinctions were observed in the areas of coverage stability and time efficiency. When analyzing coverage efficiency, the Chaotic method demonstrated a marginally higher mean coverage percentage (96.12 % ± 0.88 %) in comparison to the Waypoint method (95.46 % ± 0.24 %). However, this 0.66 % advantage is accompanied by a substantial decline in stability.

The Chaotic approach demonstrated 3.6 times higher variability (coefficient of variation 0.91 % vs. 0.25 %) and a wider range of results (95.20 % - 97.93 %) compared to the deterministic method (95.20 % - 95.87 %). This underscores the inherently probabilistic and exploratory nature of chaotic motion, in contrast to the highly predictable outcomes associated with optimized waypoints.

The most significant discrepancy was identified in time efficiency. The Waypoint method demonstrated a 2.5-fold increase in efficiency, completing the mission in an average of 13.82 seconds, while the Chaotic method required an average of 35.13 seconds. This discrepancy is also evident in the "Coverage per Minute" metric, where the deterministic, optimization-based (CRO) approach exhibited 2.5 times higher throughput (4.18 % per minute vs. 1.66 %).

The experiment yielded a discernible trade-off: the chaotic method exhibited marginally higher mean coverage (96.12 %) but was accompanied by increased unpredictability and a substantially prolonged execution time. The method with predetermined paths, in turn, guarantees high speed and exceptional stability of results, which is better for time-critical operations.

CONCLUSIONS

This paper explores the technological framework for reconfiguring UAV swarm complexes. The reconfiguration process is informed by a social interaction model and a multilevel chaotic exploration method. These components have become pivotal in ensuring adaptability and comprehensive coverage of the territory. The proposed model of social forces provides fundamental dynamic interactions between agents – repulsion, cohesion, alignment, and centroid binding – that allow them to form coordinated collective behavior patterns.

The chaotic method functions as a mechanism of stochastic exploration, guided by the attractiveness function. This phenomenon enables drones to make informed decisions regarding their trajectory, prioritizing exploration of unexplored regions and mitigating the effects of symmetry and mass accumulation.

A two-level system of counteracting stagnation (micro and macro levels) played a special role, ensuring that agents could escape from "local traps". This, in conjunction with a zonal approach to scanning, facilitated the assurance of comprehensive and systematic coverage of the complex terrain.

The simulation results confirmed the high reliability of the proposed technology. In a series of twenty experimental trials, the method exhibited a 100 % success rate in attaining a target coverage of ≥ 95 %. A comparison of the chaotic approach with the deterministic method (Waypoint Collision Avoidance) reveals that the former achieved a higher average coverage (96.12 %).

Conversely, this enhanced precision comes at the cost of temporal efficiency, as evidenced by the observation that the average mission duration was 35.13 seconds, which is 2.5 times longer than the optimized deterministic approach (13.82 seconds). A considerably higher variability of results was also documented (coefficient of variation 0.91 % vs. 0.25 %), which is an inherent property of stochastic exploration, in contrast to the high predictability of optimized waypoints.

The computational complexity analysis revealed both methods scale quadratically with swarm size ($O(n^2)$ per timestep due to neighbor detection), with the primary bottleneck being naive pairwise distance calculations. Spatial indexing techniques (k-d trees, quadtrees) can reduce complexity to O (n log n), enabling practical scaling to 50-100 drones. The critical scalability threshold for unoptimized implementations is approximately n ≈ 30-40 drones on standard hardware.

The experimental findings establish clear selection criteria for deployment scenarios. The chaotic method is optimal for coverage-critical missions in irregular complex territories where thoroughness outweighs speed (search-and-rescue, radiation mapping, unknown environments), particularly with small-to-moderate swarms ($n \leq 20$). However, its limitations include 2.5 × longer mission duration, 3.6 × higher result variability, and 13 sensitive tunable parameters requiring optimization. Conversely, the deterministic approach excels in time-critical operations (industrial accidents, tactical reconnaissance), predictable mapped environments, and large swarms ($n > 50$) where computational simplicity is essential, though it suffers from adaptability deficits in dynamic conditions and systematic coverage gaps in irregular geometries.

In the future, the technology has significant potential for development through the possible introduction of reinforcement learning methods [23], [24], [25]. This will enable agents to acquire knowledge from prior experiences, adapt their behavior to novel conditions, and automatically enhance their strategies based on feedback. The integration of social interaction mechanisms, chaotic attractors, and machine learning is projected to establish the foundation for a completely adaptive, self-learning swarm that is capable of functioning in intricate and evolving environments.

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Порівняльний аналіз хаотичного та детермінованого методів покриття території роєм дронів

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АНОТАЦІЯ

У даному дослідженні пропонується гібридний хаотично-детермінований метод управління роєм безпілотних літальних апаратів (БПЛА), що інтегрує соціальні взаємодії, такі як відокремлення, згуртованість, вирівнювання та зв'язування, із стратегією пошуку, що базується на притяганні. Дворівнева антистагнаційна система працює на рівні окремих агентів («мікро») та колективного рою («макро») для запобігання локальним мінімумам та підтримання контрольованого згладжування траєкторії. Метод використовує подвійне кондиціонування курсу для збалансування плавних траєкторій зі стохастичним дослідженням. Тим часом функція привабливості кількісно оцінює потенційні напрямки руху на основі новизни території, факторів відстані та стабільності курсу. Сили соціальної взаємодії – відштовхування, згуртованість, вирівнювання та зв'язування центроїдів – забезпечують стабільність рою та уникнення зіткнень протягом виконання місії.

Порівняльна експериментальна валідація була проведена шляхом багаторазового запуску симуляцій для кожного методу на нерегулярних багатокутних територіях. Як хаотичний, так і детермінований підходи на основі контрольних точок продемонстрували виняткову надійність місії, досягнувши порогового значення покриття цілі у всіх випробуваннях, тим самим підтвердивши повний успіх. З точки зору ефективності покриття, хаотичний метод досяг вищої середньої повноти території в порівнянні з детермінованим підходом, що є помітним поліпшенням. Однак ця підвищена точність покриття супроводжується значними витратами обчислювального часу: хаотичний метод вимагав значно довшої середньої тривалості місії в порівнянні з оптимізованим методом контрольних точок. Хаотичний підхід також продемонстрував значно вищу мінливість результатів, що відображає стохастичну природу методів, заснованих на дослідженні. Таким чином, хоча хаотичний алгоритм демонструє вищу ефективність покриття, він має нижчу часову ефективність порівняно з детермінованою базовою лінією.

Ці висновки кількісно оцінюють фундаментальний компроміс між ретельним дослідженням та ефективністю за часом в операціях з використанням автономних безпілотних літальних апаратів (БПЛА), надаючи емпіричні докази для прийняття критично важливих рішень щодо розгортання. Результати свідчать, що хаотичні методи найкраще підходять для сценаріїв, в яких пріоритетом є всебічне покриття та адаптивність, таких як пошуково-рятувальні операції, де невиявлені жертви можуть стати критичною помилкою, тоді як детерміновані підходи є більш ефективними в місіях, де час має вирішальне значення, а середовище є передбачуваним. Надійність обох методологій у поєднанні з кількісним вираженням відмінностей у продуктивності дозволяє вибирати методи на основі доказів, відповідно до конкретних операційних вимог, обмежень місії та прийнятних параметрів компромісу між ризиком, часом і точністю.

Ключові слова: інформаційні технології; ройовий інтелект; хаотичний алгоритм; мультиагентні системи; оптимізація сканування; соціальні взаємодії рою; метод протидії стагнації; оптимізація траєкторії рою

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