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Husam Al-Behadili[1], Mushreq Abdulhussain Shuriji[1], Aqeel Mahmood Jawad[2]

[1] Mustansiriyah University, Baghdad, Iraq
[2] Al-Rafidain University, Baghdad, Iraq

HYBRID OPTIMIZATION FOR QUADCOPTER DRONE SWARMING: COMBINING ANT COLONY AND BIRD FLOCKING STRATEGIES

Abstract. Although, the quadcopter drone systems have significantly impacted the drone industry, they are considered to be complicated due to the nature of cooperation in accomplishing specific missions. The complications come from the way of movements and arranges in flying tasks which need to be guided in a certain way and have the skill of obstacle dodging. In this research, a developed proposal of a hybrid robot biological swarming algorithm introduced a significant enhancement in swarming rules and blended between the leadership and members' movement control. This enhancement comes from combining two major abilities from observing the selected biological swarms. From the bird flocks the quadcopter drone will have the capability of formations, obstacle avoidance, and safe distance keeping while flying while preserving the ability to alter directions and speed. However, due to the lack of ability to guide the quadcopter drones into specified stored locations which limits the potential applications, the use of ant colony swarm inspiration has solved this issue. The developed algorithm is suitable for a wide range of real-time applications such as firefighting in open lands, rescue missions, delivery, and scanning in time of disasters, and agricultural field like air scanning, health status, and irrigation condition.

Keywords: robot swarming; biological inspiration; biomimetic; quadcopter drone; hybrid swarming.

1. Introduction

Currently, the mobile drone swarming field has attracted much research due to the large scale of applications that could benefit the industrial, educational, and business systems. These researchers carried out many applications in this field, such as factory and warehouse facilities, autonomous flying, astronomy, underwater, etc. The system with multi-reactive drones able to self-formation behavior is considered complex compared to a system with a singular drone. In a self-formation system, the flocking is the natural illustration for the system; such a system is been found in many biologically stimulated systems [1]. The flocking scheme depends on a collective action, that embraces many cooperating drone movements in a joint direction. These movements as a solo interactive group are subject to preserving a minimum distance among units, evading obstacles, and being aware of solo units of the orientation [2–4]. These individual units' behavior within the drone herd has captured the devotion of researchers in many fields, including robotics [5, 6], physics [7, 8], biology [9, 10], and control and communication engineering [11, 12]. The backbone of modeling multi-mobile quadcopter drone systems is examining the mechanical instructions that rule these depending systems on the algorithms of leaderless [13]. The flock of quadcopter drones design and modeling of a swarm robot be contingent on interaction instructions in autonomous transportable. Also, declare valuable planes for enhancement of multi-self-controlled quadcopter drones [14]. In [15], the flocking of one leader for swarm robots has been presented. It revealed a developed underwater flocking using MATLAB simulation to avoid a 3D obstacle but with a lack of guide into a specific location. [16] has proposed a K-means algorithm for the swarming robots' aggregation behavior using Webots simulation. It demonstrated a developed system with avoiding skills in several obstacles with no guidance for flock swarming. [17] provided a Triangle Formation (TF) algorithm for distributed control for flocking. This method enhances obstacle avoidance with no guide for an intended direction and location. In [18], an ant colony algorithm has been proposed for a path-planning robot. It provided an optimum path pursuit for swarming with no skill of evading obstacles. [19] presented an extensive review of swarming intelligence (SI) for multi-robots focusing on many natural swarms like ants. This research has highlighted the ant colony is a bile to determine and direct the robots into a specific location in an efficient way and it has no avoidance for obstacles. In [20], a robot swarming localization task has been presented. It aimed to accelerate the localization of the target, but it had no skill or ability to avoid obstacles.

This paper examines and analyzes the proposed hybrid scheme for takeoff, flying, and landing for quadcopter drones swarming with the skill of avoiding collision, flying safely, and fine execution of reaching specific locations and directions with a thoughtful design of ad-hoc communication among the quadcopter units within the flock. The paper's layout contains the introduction, autonomous mobile drones, solo drone basic motion tasks, swarming behavior of biomimetics, implementation, and design of the suggested swarming and communication scheme, outcome results and discussions, and conclusion.

2. Autonomous Robots and Swarming Biomimetic

Firstly, autonomous robots are described as electromagnetic instruments with programmed skills to achieve many objectives. They are been used in many industries with human-free projects due to their performance flexibility and efficiency. Self-controlled drones (mobile robots) should be able to deal with many tasks such as; having complete mapping data knowledge for their nearby obstacle and operational locations for avoiding and flying, accurately and accordingly route-finding (navigation) depending on their collected and stored environmental info from sensors, precise predefined missions and accurate autonomous arrangements and self-control with no human disturbance, and optimum path routing were the drone can alter and maneuver its upcoming move [21-23]. Many science fields integrated into designing drones like; robot kinematics, locomotion, control, information theory, artificial intelligence (AI), etc. The control system's block diagram of an autonomous drone is presented in Fig. 1 [24].

In a single drone, there are three basic motions, point-to-point or point stabilization, trajectory tracing, and path-following and they are shown in Fig. 2.

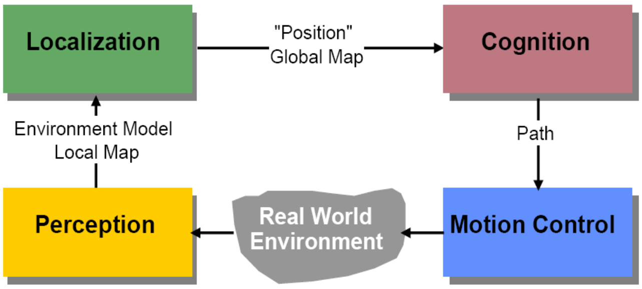
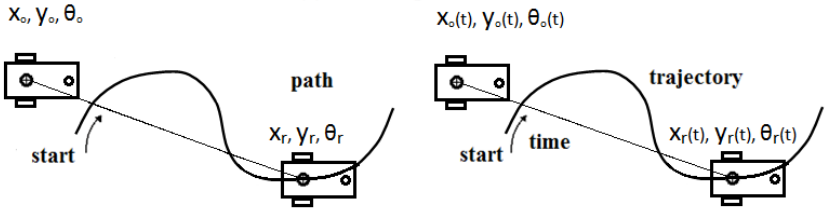


Fig. 1. The Control system of the mobile robot (drone)

(a) Point-to-point



(b) Geometric path following

(c) Timed trajectory tracking

Fig. 2. The three basic motions of a robot

In point-to-point motion, a robot starts from the initially recognized configuration to reach a required configuration. In the trajectory tracking motion, the robot tracks a trajectory from a reference point. In other words, the track of a trajectory is the geometric trail with the motion timing that started from a cartesian space's initial configuration. The tracking control pathway is responsible for the robot to follow asymptotically. While in the path following the track is the geometric pathway with the motion but without any timing that started from a cartesian space's initial configuration. The controller assures the robot's specific route and stays with it regardless of the duration required to track and reach the pathway.

A biological system, like a bird flock or an ant colony, moves harmoniously and follows nearby groups. Both are systematized and synchronized in their movements. To design a quadcopter drone based on a biological system of bird flocks, extensive monitoring is vital to attain a valuable data control scheme. After the nonstop monitoring of bird flock, there are significant rules were extracted. The rules are:

- Collision avoidance rule: this rule has a priority of being the most significant effect on the way drones fly. The individual drone must avoid crashing neighboring drones, maintain minimum separation distance, and evade environmental obstacles.
- Alignment velocity rule: the drone must synchronize its velocity with neighboring drones when the drone not performing the first rule. Also performing a high-speed attraction with the drone's flock to dodge any isolation.
- Centering of flock rule: the drone must fly close to the neighboring drones to avoid solo flying with a coherence group flying. The drone should always fly on the way to the center of the quadcopter flock.

These are the major rules to design quadcopter drones inspired by bird flock swarming which are appropriate for obstacle avoidance environments, accommodating navigation, and energy-efficient route strategy tasks.

In the ant colony, the swarming rules for drones are as follows:

- Stigmergic communication rule: this rule involves virtual pheromones used like map sharing and GPS markers to enhance navigation, indirect organization, and mission allocation.
- Positive and negative feedback rule: in this rule, positive feedback should increase electing likelihood, guarantee the finest path, and efficacy to strengthen successful routs or missions. The negative feedback rule implements pheromone vanishing, in other words, data decay for stopping the stagnation, adaptation due to environmental changes, and confirming constant exploration.
- Adaptive task allocation rule: depending on real-time requirements and adjusting resources, the drones will ensure role-switching for all the flying groups within the flock with high responsiveness.

These rules are significant in designing a quadcopter drone based on the biological swarming of ant colonies that are suitable for search, monitoring, surveillance, and warehouse automation missions, etc.

3. Propose of Hybrid drone Swarming

3.1. Background: ACO and Bird Flocking

- Ant Colony Optimization (ACO): Inspired by the foraging behavior of ants, ACO is a metaheuristic algorithm used for finding optimal paths or solutions. Ants deposit "pheromones" on paths they traverse. Subsequent ants are more likely to follow paths with higher pheromone concentrations, leading to a collective discovery of efficient routes. The "food source" represents a potential victim location, and the pheromone represents the likelihood of that location being relevant. ACO excels at finding good solutions in complex, graph-like environments. However, it can be slow to converge and can be susceptible to premature convergence if pheromone evaporation isn't handled correctly. In our drone application, ACO guides the swarm towards potential targets.

- Bird Flocking (Boids): This algorithm simulates the collective motion of bird flocks. It's based on three simple rules:
  - Separation: Avoid crowding nearby flock-mates.
  - Alignment: Steer towards the average heading of nearby flock-mates.
  - Cohesion: Move towards the average position of nearby flock-mates.

Bird flocking is excellent for decentralized, reactive movement. It allows drones to quickly adapt to changing environments and maintain group cohesion. However, it can be prone to getting stuck in local minima and lacks a clear goal-seeking mechanism without additional guidance.

3.2. The Weighted Directional Approach

Our approach combines these two strengths by creating a weighted average of the directions calculated by each algorithm. Let's dissect how this works:

3.2.1 Ant Direction Calculation:

ACO is based on probabilistic decision-making, where artificial ants traverse a graph and update pheromone trails to guide future ants. The key equation governing the direction of movement in ACO is the **transition probability** equation as shown in Eq. (1), which determines the likelihood of an ant moving from the drone's current location to node the nearest food source (potential victim location):

$$P_{ij}(t) = \frac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_{k \in N_i} [\tau_{ik}(t)]^{\alpha} \cdot [\eta_{ik}]^{\beta}}, \qquad (1)$$

where $P_{ij}(t)$ is probability of an ant moving from node i to node j at time t;

$\tau_{ij}(t)$ is Pheromone intensity on edge (i,j) at time t;

η_{ij} is Heuristic value (often inverse of distance: $\eta_{ij} = 1/d_{ij}$), representing desirability;

α is Pheromone influence parameter (controls the importance of pheromone trails);

β is Heuristic influence parameter (controls the importance of distance);

N_i is Set of possible next nodes from i.

This equation ensures that ants are more likely to follow paths with stronger pheromone trails and shorter distances, leading to an emergent collective optimization behavior.

3.2.2 Bird Flocking Influence:

The bird flocking component is implemented through the "alignment" and "cohesion" rules. Additionally, the population-based optimization approach to evolve the Boids parameters themselves were applied in this article [25]. Each drone adjusts its movement based on the positions and headings of its nearby flock-mates. This ensures that the swarm maintains a cohesive group and reacts to local environmental changes.

The direction calculation equations of BFO in this article are derived from the flocking behavior model based on [25], which is inspired by birds' swarming motion. Here are the key equations related to direction calculations:

i. **Collision Avoidance (Rule 1)**:
Each bird (or robot) avoids colliding with neighbors by maintaining a minimum separation distance:

$$d_r(t+T) = \Sigma_{j=1}^{n_r} \frac{(p_j - p_i)}{|p_j - p_i|}, \qquad (2)$$

where p_i is the position of the i-th bird; p_j is the position of the j-th neighbor, n_r is the number of neighbors within the repulsion zone.

ii. **Velocity Alignment (Rule 2)**:
Each bird aligns its velocity with the average velocity of its neighbors:

$$d_o(t+T) = \frac{1}{n_o} \sum_{j=1}^{n_o} v_j \,, \qquad (3)$$

where v_j is the velocity of the j-th neighbor; n_o is the number of neighbors in the orientation region.

iii. **Flock Centering (Rule 3)**:
Each bird moves towards the center of its neighboring group to maintain cohesion:

$$d_a(t+T) = \frac{1}{n_a} \sum_{j=1}^{n_a} (p_j - p_i), \qquad (4)$$

where n_a is the number of neighbors in the attraction region.

iv. **Overall Direction Calculation**:
If a bird has neighbors in both alignment and attraction zones, the new direction is computed as:

$$d_i(t+T) = \frac{1}{2} d_o(t+T) + \frac{1}{2} d_a(t+T), \qquad (5)$$

If there are no neighbors, the bird continues in its current direction:

$$d_i(t+T) = v_i(t). \qquad (6)$$

v. **Final Position Update**:
Once the new direction is calculated, the position is updated using:

$$p_i(t+T) = v_i(t+T) \cdot TU + p_i(t), \qquad (7)$$

where U is the bird's speed; T is the time step.

These equations describe how each robot in the swarm adjusts its direction dynamically based on its neighbors' positions and velocities according to the BFO.

3.2.3 Combining ACO and BFO

Hybrid Approach: The ACO guides the swarm towards potential targets, while BFO optimizes the Boids parameters to ensure cohesive and efficient flocking behavior.

Parameter Synchronization: The BFO algorithm can be run periodically to adapt the Boids parameters to changing environmental conditions or swarm objectives.

Weighted Average: This is the core of the combined method. We're calculating a combined direction using:

$$d_f(t+T) =$$
$$= \gamma \cdot d_{aco}(t+T) + (1-\gamma) \cdot d_{bfo}(t+T). \quad (8)$$

The d_{aco} and d_{bfo} parameters control the relative influence of each algorithm. A higher d_{aco} by choosing $0.5 < \gamma \leq 1$, prioritizes the search for potential victims (guided by pheromone trails), while a higher d_{bfo} by choosing $0 < \gamma \leq 0.5$, emphasizes group cohesion and reactive movement. The final direction d_f is normalized to ensure it has a unit length.

Boundary Handling: The method includes boundary checks to keep the drones within the defined search area. This is crucial for real-world deployment.

Pheromone Update: When a drone reaches a potential victim location (food source), it deposits pheromone at its current location. This reinforces the path and guides other drones towards that area.

3.2.4 Advantages of the Combined Approach

Enhanced Exploration: The ACO component encourages exploration of potential victim locations, while the bird flocking component ensures that the swarm doesn't get stuck in local minima and continues to cover the search area.

Adaptive Behavior: The changing of conditions leads to the adaptation of the swarm. The ACO component rapidly guides the drones when a new possible target is spotted. The flocking bird will assist the swarm in navigating around any encountered obstacles.

Robustness: The swarm becomes much robust to failures when two algorithms are combined. In a certain scenario, if one algorithm crashes, the other will prevail and deliver control in guidance.

Decentralized Control: The swarm is extra resilient to miscommunication due to the fact of the decentralized algorithms' advantage of both bird flocks and ACO. They are capable of realizing without a central control need.

Improved Coverage: The combination of search and cohesion results in more comprehensive coverage of the exploration area.

To sum of all, the combined scheme of both Bird flock and ACO delivers a promising outline in designing adaptive and robust quadcopter swarms, which are skilled for rescue and search operations and navigations.

4. Experiment Description

A comparison simulation study has been carried out using MATLAB 2024a to assess the performance of the suggested hybrid technique. Inside the simulation suit, three target locations have been defined. Also, three control sets have been presented: Ant Colony Optimization (ACO) for target-seeking behavior illustration, Bird Flocking Optimization (BFO) for cohesive flocking behavior illustration, and the proposed Hybrid scheme. Fig. 3 (a) presented all sets with matching start positions of agents (ants, birds, and drones). The simulation permitted movement pattern, divergence, and convergence observation in the direction of the locations of the targets via executions a fixed number of iterations for each group. A standard pheromone update has been implemented for the ACO set with evaporation rules with high prior order to the nearest target for a direct path without the attention of coordination of the inter-agent. Standard cohesion, alignment, and separation rules for BFO sets have been implemented to preserve integrity but with the absence of obvious target-seeking behavior. The suggested hybrid approach has the skill of flocking characteristics, target-seeking, proximity among the agent grouping, nearest target approach, and dynamic balancing between the flock consolidation and target method.

5. Results and Discussions

5.1. Comparative Analysis of Path Optimization Methods

Our experimental investigation revealed intriguing patterns across three distinct approaches to quadrotor path optimization. The results highlight key differences between Ant Colony, Bird Flocking, and our proposed hybrid method, each demonstrating unique characteristics in solving the path planning challenge.

5.2. Performance Metrics Analysis

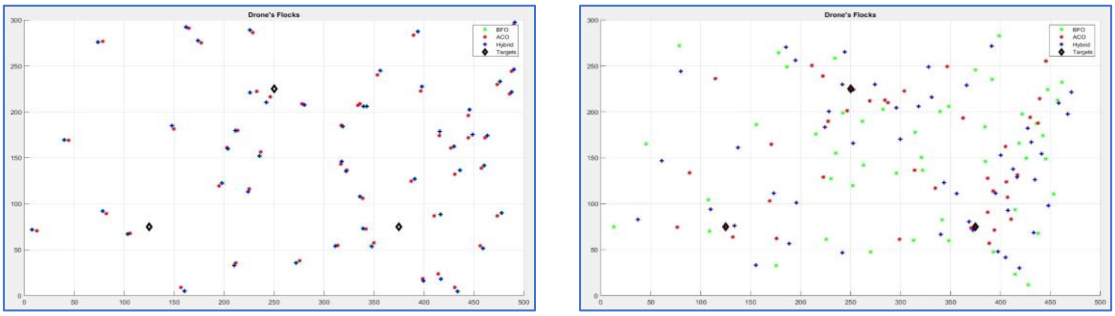
In terms of convergence speed, as shown in Table 1 the Ant Colony algorithm demonstrated superior efficiency, completing its optimization in just 337 iterations. While our hybrid method required slightly more computational effort at 438 iterations, it maintained consistent performance. Bird Flocking, however, consistently reached the maximum iteration limit of 1,000, indicating potential limitations in its target-seeking capabilities. These behaviors can be shown in Fig. 3 (a) to Fig. 3 (f).

Table 1 – **The comparison among the different methods**

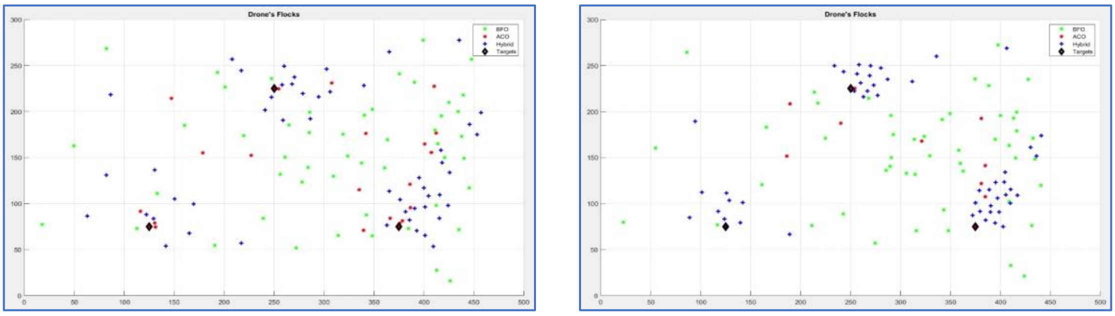
Metric	**Ant Colony**	**Bird Flocking**	**Proposed Method**
Iterations	337.25 ± 98.06	1000 ± 0	438.07 ± 61.2
Dist. from Target	11.56 ± 6.66	101.43 ± 11.39	16.6 ± 0.86
Path Length	336.25 ± 98.06	3045.61 ± 144.54	270.87 ± 56.8
Dist. among agents	19.45 ± 10.67	60.55 ± 12.92	22.09 ± 0.91
Swarm Density	4.488 ± 3.3001	0.0047 ± 0.0019	0.0165 ± 0.001

Target accuracy measurements revealed that Ant Colony achieved the closest approach to designated targets, with an average distance of 11.56 units. Our hybrid method followed closely at 16.6 units, while Bird Flocking showed significantly less precision with an average distance of 101.43 units. These differences reflect each algorithm's inherent balance between precision and practical constraints.

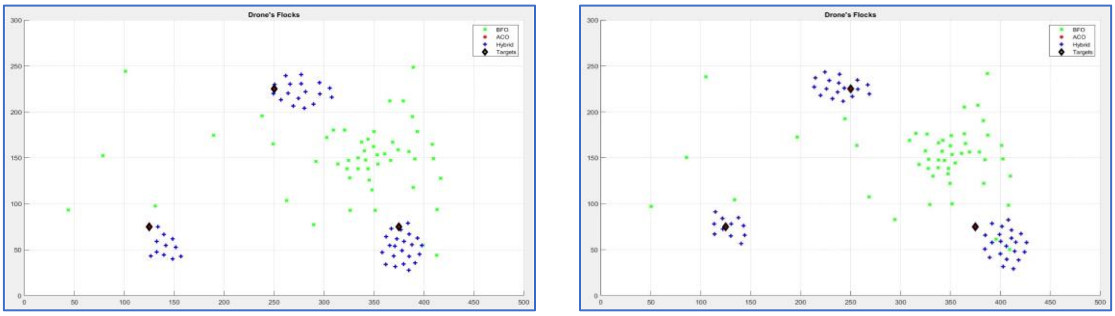
Perhaps the most striking finding emerged in path optimization, where our hybrid method excelled by generating the shortest routes (270.87 units) while maintaining stable trajectories. This outperformed both the Ant Colony (336.25 units) and Bird Flocking (3045.61 units) approaches, demonstrating the effectiveness of combining pheromone-based guidance with flocking behavior.



a – Drones’ behavior at time frame iteration = 1 b – Drones’ behavior at time frame iteration = 250



c – Drones’ behavior at time frame iteration = 350 d – Drones’ behavior at time frame iteration = 500



e– Drones’ behavior at time frame iteration = 750 f – Drones’ behavior at time frame iteration = 1000

Fig. 3. The location of the drones according to the optimization methods

5.3. Swarm Behavior Characteristics

The algorithms showed distinct patterns in managing group dynamics. Our hybrid method maintained a balanced swarm density of 0.0165 units as shown in Table 1, ensuring practical spacing between quadrotors. This contrasts sharply with Ant Colony's dense clustering (4.488 units) and Bird Flocking's sparse distribution (0.0047 units).

5.4. Practical Implications

These findings demonstrate that while Ant Colony excels in raw target acquisition, our hybrid approach offers the most practical solution for real-world applications. It successfully balances efficiency with necessary physical constraints, maintaining safe distances between quadrotors while achieving reliable path optimization. This makes it particularly suitable for applications requiring both precision and practical safety considerations.

Conclusions

The simulation results and outcomes presented substantial differences in the effectiveness and the behavior of each scheme.

The ACO set revealed a leaning to converge straight to the direction of the nearest target with habitually spatially dispersed and isolated of the individual agents. In the BFO group, a cohesive flock has been maintained, while it fails to fly next to the target locations effectively, and within the simulation district it lacked the remaining localization and directional intent. However, the projected hybrid approach has successfully adopted both the flocking behavior and target-seeking simultaneously.

The method designed separate groups of agents, and then each group correlated with a specific target location, depending on an integration of proximity to the nearest target and inter-agent distance. The significance that comes from this method is the groups' dynamic behavior; the agents often steer their trajectories to join nearby candidates, provide a flock consolidation via presenting a willingness to delay direct target approach. Once a sufficient number of agents are reached within a group, the flock is harmonized in its movement in the direction of the nearest target. These behaviors are illustrated in Fig. 3 (b) to Fig. 3 (d). Unlike the ASO and BFO, the proposed hybrid scheme offered an enhancement in the dynamic and distributed system behavior, where the agents adopted nonstop movement around the locations of the target and sustained a separation level among agents to avoid collisions as they presented in Fig. 3 (g) to Fig. 3 (f). The results have shown the significance of the proposed hybrid swarming method through balancing the strengths of both ACO and BFO by offering adaptive and robust solutions in target acquisition and multi-agent navigation.

The capability to adjust the trajectories dynamically and combine new agents into the flocking group signifies the substantial benefit over the individualistic behavior of ACO and the directionless of BFO behavior.

In conclusion, the proposed hybrid robot swarming provides an enhancement in the field of swarming. The inspiration comes from combining two natural biological systems: Bird Flock and Ant Colony. The significance of the suggested scheme is that it offers an adaptive and robust solution in target acquisition and multi-agent navigation.

The quadcopter drone will have the capability of formations, obstacle avoidance, and safe distance keeping while flying while preserving the ability to alter directions and speed. It also has the talent of determining a certain direction and location.

The proposed hybrid quadcopter drone biological swarm has the ability to perform a comprehensive controlled flying system by combining the two methodologies.

The suggested hybrid approach for quadcopter drones is suitable for a wide range of quadcopter drone real-world scenario applications such as fire detection and fighting in open remote lands, quick response to rescue missions, delivery, and scanning in time of disasters, and air scanning for crops like health status and irrigation conditions.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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ABOUT THE AUTHORS / ВІДОМОСТІ ПРО АВТОРІВ

Аль-Бехаділі Хусам – PhD (інформаційна та електрична інженерія), викладач кафедри електричної інженерії, інженерний факультет, Університет Аль-Мустансірія, Багдад, Ірак
Husam Al-Behadili – PhD (Information and Electrical Engineeering), Lecturer, Electrical Engineering Department, College of Engineering, Mustansiriyah University, Baghdad, Iraq;
e-mail: husam.albehadili@uomustansiriyah.edu.iq; ORCID Author ID: https://orcid.org/0000-0002-4338-2825;
Scopus Author ID: https://www.scopus.com/authid/detail.uri?authorId=56566756900.

Шуріджі Мушрек Абдулхуссейн – PhD (електротехніка / телекомунікації), викладач кафедри електричної інженерії, інженерний факультет, Університет Аль-Мустансірія, Багдад, Ірак
Mushreq Abdulhussain Shuriji – PhD (Electrical Engineering \ Communication), Lecturer, Electrical Engineering Department, College of Engineering, Mustansiriyah University, Baghdad, Iraq;
e-mail: mushreq@uomustansiriyah.edu.iq; ORCID Author ID: https://orcid.org/0000-0002-4202-5543;
Scopus Author ID: https://www.scopus.com/authid/detail.uri?authorId=57211335244.

Джавад Акіл Махмуд – PhD (електрична, електронна та системна інженерія), викладач кафедри інженерії медичної апаратури, факультет інженерії та інженерних технологій, Університет Аль-Рафідейн, Багдад, Ірак.
Aqeel Mahmood Jawad – PhD (Electrical, Electronic and Systems Engineering), Lecturer, Medical Instrumentation Techniques Engineering Department, College of Engineering and Engineering Techniques, Al-Rafidain University, Baghdad, Iraq;
e-mail: aqeel.jawad@ruc.edu.iq; ORCID Author ID: https://orcid.org/0000-0003-1671-7607;
Scopus Author ID: https://www.scopus.com/authid/detail.uri?authorId=57195290010.

Гібридна оптимізація для ройового керування квадрокоптерними дронами: поєднання стратегій мурашиної колонії та зграї птахів

Х. Аль-Бехаділі, М. А. Шуріджі, А. М. Джавад

Анотація. Незважаючи на те, що системи квадрокоптерних дронів суттєво вплинули на індустрію безпілотників, вони вважаються складними через характер взаємодії під час виконання конкретних місій. Складність зумовлена способом руху та організації польоту під час виконання завдань, які повинні здійснюватися за певними правилами та потребують здатності уникати перешкод. У цьому дослідженні запропоновано вдосконалений гібридний алгоритм біологічного ройового керування роботами, який забезпечує значне покращення правил формування рою та поєднує керування рухом лідера і учасників групи. Це вдосконалення досягнуто шляхом об’єднання двох ключових властивостей, запозичених зі спостережень за біологічними роями. Від зграї птахів квадрокоптерні дрони отримують здатність формувати польотні формації, уникати перешкод і підтримувати безпечну дистанцію під час польоту, зберігаючи при цьому можливість змінювати напрямок і швидкість. Однак через відсутність можливості спрямовувати квадрокоптерні дрони до заздалегідь визначених збережених точок, що обмежує потенційні сфери застосування, цю проблему було вирішено шляхом використання принципів поведінки мурашиних колоній. Розроблений алгоритм придатний для широкого спектра застосувань у реальному часі, таких як гасіння пожеж на відкритих територіях, рятувальні операції, доставка, сканування під час надзвичайних ситуацій, а також для сільського господарства — зокрема аеросканування полів, моніторинг стану рослин та умов зрошення.

Ключові слова: роїння роботів; біологічне натхнення; біоміметика; квадрокоптерний дрон; гібридне роїння.