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RESEARCH ARTICLE

Gravitational Search Algorithm Swarm-Based UAV Reconnaissance for Multiple Targets Detection in Unknown Environment

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ABSTRACT Target detection in an unknown environment is a crucial aspect of reconnaissance using a swarm of unmanned aerial vehicles (UAVs). An efficient target detection technique is required to minimize the number of iterations for searching and maximize the coverage area with respect to the number of iterations and detected targets. This paper proposes a gravitational search algorithm (GSA) swarm-based UAV reconnaissance scheme to detect targets in an unknown environment. Additionally, different GSA-based searching methods are analyzed to identify the most efficient one with the minimum number of iterations and maximum coverage. Extensive simulations are performed, and the results of the proposed scheme are compared with existing search schemes. The results demonstrate that the proposed GSA swarm-based detection scheme requires fewer iterations and provides greater area coverage than existing UAV reconnaissance schemes for target detection in an unknown environment.

INDEX TERMS UAV reconnaissance, gravitational search algorithm, swarm, unknown environment.

I. INTRODUCTION

Unmanned aerial vehicles (UAVs), commonly known as drones, are widely used for security, reconnaissance, and remote sensing applications [1], [2]. Swarm UAVs are automated and unmanned swarm-robot systems. Research on swarm UAVs is essential to enhance their performance. UAVs can overcome the limitations of terrestrial systems in terms of accessibility, speed, and reliability in surveillance, making them valuable for reconnaissance purposes [3], [4]. The effectiveness of swarm UAVs depends on the extent to which the capabilities and actions of individual UAVs in the swarm are synchronized. However, swarm UAVs cannot outperform a single UAV without proper control strategies and decision-making methods.

UAVs face various challenges, such as collisions and issues at temporal, spatial, and task levels within a swarm, making it difficult to complete tasks efficiently [5]. Effective coordination and autonomous control are essential among UAVs in the swarm when performing surveillance in unknown or uncertain environments. Biological swarm behavior algorithms have proven to be effective for coordinating and autonomously controlling UAVs in swarms, especially in unknown or complex environments [6].

Swarm behavior can be inspired by natural phenomena, complex swarm behaviors observed in various aspects

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of nature, or objects with different characteristics. A biological swarm not only moves in a coordinated and orderly manner but also responds to external impacts. Biological swarm intelligence arises from diverse intelligent behaviors and characteristics of distribution and self-organization. Various swarm intelligence algorithms inspired by natural and mechanical phenomena have been proposed, including particle swarm optimization (PSO) [7], ant colony optimization (ACO) [8], penguin search optimization algorithm (PeSOA) [9], genetic algorithm (GA) [10], firefly algorithm [11], and gravitational search algorithm (GSA) [12]. Recently, optimization techniques based on swarm algorithms have been employed to address complex optimization problems, including swarm robotics, telecommunications, and image processing [13].

UAV reconnaissance based on swarm UAVs has also been investigated to improve performance by using multiple UAVs [13], [14], [15], [16], [17], [18], [19]. Multiple swarm-based UAV reconnaissance approaches were proposed to overcome the limitations of a single swarm [15], [16], [17], [18], [19]. Probabilistic and altitude-based UAV reconnaissance was conducted to explore multiple parts of the search area simultaneously for known targets in [15], [16], [17], and [18]. Known targets refer to scenarios where the environment and target positions are predefined for the UAVs. Usman et al. proposed a UAV reconnaissance technique using a hybrid algorithm in [19]. Their hybrid algorithm for known targets combined PSO and penguin search optimization algorithms. Other researchers assumed that the positions of all targets were known before searching [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19]. Under this assumption, the primary goal of these studies was to minimize the search time for known targets using different algorithms. However, this assumption is not practical, as the positions of the targets and the nature of the environments are not necessarily known to the swarm. This highlights the need for reconnaissance techniques that dynamically adapt to unknown environments, which is addressed in our proposed technique.

An unknown target implies that UAVs lack prior knowledge of the environment and the target's position. Consequently, swarm-based UAV reconnaissance for detecting unknown targets becomes a more viable solution, as the target's location and environment are typically unknown to the swarm in practical scenarios. Cai and Yang introduced a PSO approach for detecting obstacles in unknown environments using the cooperative behavior of multiple robots [20]. However, their work did not propose any technique for detecting unknown targets. In another study, Li et al. aimed to detect targets using a swarm of robots in an unexplored environment [21]. They developed a hybrid search algorithm that combined a random search algorithm with a dynamic PSO (DPSO) algorithm. The entire search area was divided into sub-regions to enhance performance, while the authors claimed that the environment was unknown. The division of the search area into predefined sub-regions suggests that some prior knowledge of the environment was assumed. Furthermore, a bean-optimization-based cooperative method for target detection by swarm UAVs in unknown environments was proposed by Zhang and Ali [22]. However, this study did not evaluate the search time or coverage area concerning the number of optimization iterations, which are critical metrics for practical applications.

The primary challenges in previous swarm-based UAV reconnaissance schemes lie in detecting targets in unknown environments within minimal time and computational resources. This is particularly critical, as UAVs have limited computational power and battery capacity [2], [3], [4], [23]. These constraints underscore the need for effective swarm-based UAV reconnaissance techniques that can efficiently detect targets in unknown environments while minimizing search time.

One of the key advantages of swarm reconnaissance is the ability of multiple UAVs to explore different areas simultaneously, significantly increasing the coverage area and reducing the time required to locate an unknown target. Furthermore, UAVs can dynamically adapt their search patterns in response to obstacles or new data, making them highly effective in uncertain conditions. By distributing the search load, individual UAVs can optimize their energy consumption, which extends their operational time. Additionally, swarm reconnaissance can handle multiple objectives simultaneously, such as obstacle avoidance, mapping, and target detection, making it a versatile and practical solution for target detection in unknown environments.

II. MOTIVATION AND CONTRIBUTIONS

Motivated by the aforementioned challenges, this study proposes a swarm-based UAV reconnaissance scheme using the gravitational search algorithm (GSA). GSA variants have been developed to address specific optimization challenges, such as GSA combined with PSO, quantum GSA, binary GSA, multimodal GSA, and multi-objective GSA. Agents or problem variables can be represented in different forms, with the most common types being continuous (real-valued), binary-valued, discrete, and mixed representations. Different GSA variants have been designed to accommodate these representations, enabling the algorithm to tackle a wide range of problems effectively. Similarly, optimization problems are often categorized based on their objective functions, such as constraint-based, multimodal, and multi-objective problems. GSA variants have been specifically developed to solve these types of issues, demonstrating the algorithm's versatility and adaptability in addressing diverse optimization challenges [24].

The proposed scheme adopts the conventional GSA to assess its feasibility and performance for searching unknown targets. Additionally, previous studies have not thoroughly analyzed the required number of search iterations and the coverage area, considering the number of iterations used to detect unknown targets. To address this research gap, the proposed scheme is applied to search for unknown

TABLE 1. Comparitive analysis of the existing UAV-based target search techniques.

Literature	Search Algorithm	No. of UAVs	No. of Targets	Target Location
[14]	DPCHA	Swarm	Multiple Targets	Known
[15], [18]	IHPTSA	Two UAV's	Multiple Targets	Known
[16], [17]	IRST	Single UAV	Single Target	Known
[19]	PSO & PeSOA	Swarm	Multiple Targets	Known
[20]	PSO	Swarm	Multiple Targets	Known
[21]	Hybrid (DPSO & Random)	Swarm	Multiple Targets	Unknown
Proposed System	GSA	Swarm	Multiple Targets	Unknown

targets, providing a detailed performance evaluation and demonstrating its effectiveness in overcoming the identified challenges. For this study, the authors have selected the traditional GSA to establish a baseline for feasibility and performance comparison. The traditional GSA is chosen due to its simplicity, robustness, and proven ability to effectively balance exploration and exploitation in dynamic search spaces like unknown environments. By focusing on the conventional GSA, we aimed to ensure that the results remain generalizable and not influenced by the complexities of specific variants. The performance benefits demonstrated in this study highlight the foundational strengths of GSA, providing a platform for future work to explore advanced variants in more complex scenarios.

Importantly, GSA enables the specification of four key parameters for each mass (agent): position, inertial mass, active gravitational mass, and passive gravitational mass. The position of a mass corresponds to a potential solution to the problem, and a fitness function is used to determine the gravitational and inertial masses [25], [26]. This mass represents the optimal solution in the search space. Furthermore, the GSA is founded on the principles of Newtonian gravitation and motion [25], [26], where the gravitational force is directly proportional to the mass. These properties make GSA suitable for swarm-based UAV reconnaissance in searching for unknown targets. Additionally, the conventional random search algorithm and a hybrid algorithm are compared with the proposed GSA-based swarm reconnaissance scheme. While other conventional reconnaissance schemes, such as PSO, are effective for searching known targets [7], [8], [9], the hybrid and random search algorithms are better suited for detecting unknown targets.

Notably, the hybrid algorithm, consisting of random search and DPSO, requires fewer iterations than the random search algorithm to locate unknown targets [21]. For a comprehensive evaluation, both the hybrid and random search algorithm-based UAV reconnaissance schemes are compared with the proposed GSA-based scheme.

Furthermore, the main contributions of this work are summarized as follows:

- GSA swarm-based UAV reconnaissance to search multiple unknown targets is proposed. Additionally, different GSA-based search strategies are developed to investigate the performance of the proposed GSA-based unknown target(s) search scheme.
- Two-dimensional (2D) model is analyzed based on the simulation results to examine the proposed scheme's feasibility and superiority over conventional search schemes for multiple unknown targets.
- The performance is analyzed in terms of the number of iterations with respect to the number of targets and the coverage area with respect to the number of iterations.
- The performance of the proposed scheme is compared with the conventional swarm-based reconnaissance schemes, which are suitable for searching unknown targets (e.g., hybrid and random search algorithms).

III. COMPARITIVE ANALYSIS WITH THE EXISTING LITERATURE

Many research studies are currently being conducted to optimize target detection by using a swarm of UAVs. Probabilistic and altitude-based UAV reconnaissance was performed to explore multiple parts of the search area simultaneously for targets in unknown environments, with

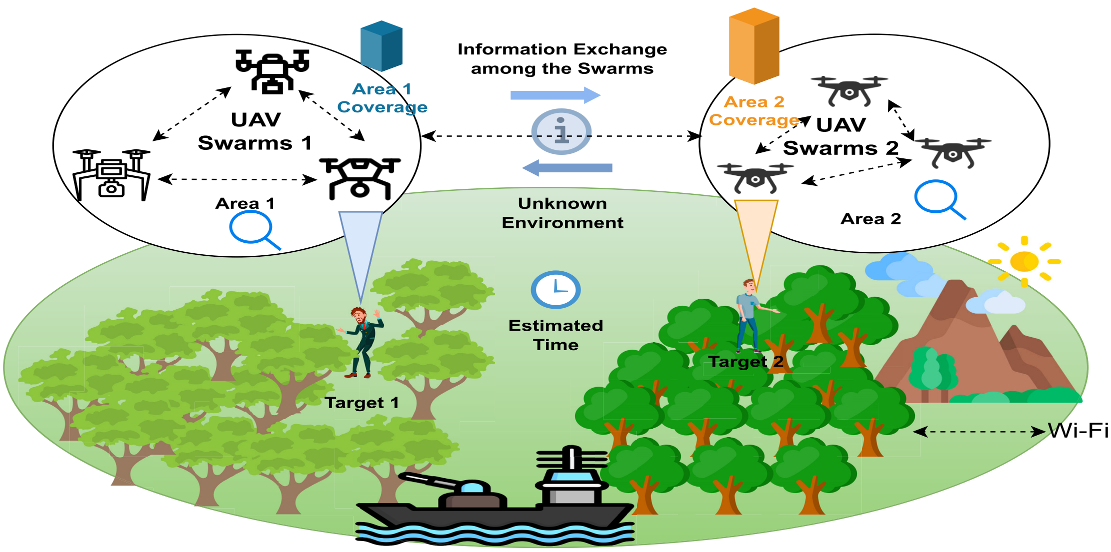


FIGURE 1. System model of proposed GSA swarm-based UAV reconnaissance.

target locations that were predefined to the UAVs [15], [16], [17], [18]. A dual-pheromone clustering hybrid approach (DPCHA) was proposed in [14] for swarm-based target detection along with map coverage and network connectivity. Later, an improved hierarchical probabilistic target search algorithm (IHPTSA) based on the collaboration of UAVs at different altitudes was proposed in [15]. A wide field of an infrared search system (IRST) was proposed in [16], [17] that detects the targets through the infrared radiation differences between the target and its background. Usman et al. proposed a UAV reconnaissance technique using a hybrid algorithm. The hybrid algorithm for known targets consisted of using particle swarm optimization (PSO) and penguin search optimization algorithms [19]. A number of studies assumed that all the locations of targets are known prior to the search [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19]. Under this assumption, the main purpose of these investigations was to minimize the search time of known targets with different algorithms. However, the assumption that the target positions are known is not feasible in a practical scenario.

Another study was performed by Li et al. to detect targets using a swarm of robots in an unknown environment [21]. They proposed a method to improve the target detection performance using a hybrid search algorithm. This algorithm was built by combining a random search algorithm and a dynamic particle swarm optimization algorithm (DPSO), and the entire area was divided into different sub-regions. The sub-regions were described to the swarm, which means that the environment was known to the swarm. Moreover, there are some vision-based reconnaissance techniques previously proposed in [27], which are almost overtaken by the recent reinforcement learning [28] and neural networks [29] based techniques in UAV systems. A comparative analysis of the existing UAV-based target search techniques is provided in TABLE 1.

Conclusively, the main challenges associated with swarm-based UAV reconnaissance are unknown target detection within a minimum time, reducing the number of iterations, and maximizing the convergence area because UAVs have limited computational power and battery capacity [2], [3], [4], [21], [27], [28], [29]. Effective multiple swarm-based UAV reconnaissance is required for target detection in an unknown environment with minimum search time, reduced iteration, and maximum coverage area to address these shortcomings.

IV. PROPOSED GSA SWARM-BASED UAV RECONNAISSANCE SYSTEM

This section describes the GSA swarm-based UAV reconnaissance scheme for searching and detecting unknown targets in an unknown environment. The proposed system model to detect unknown targets is shown in FIGURE 1. This model uses a swarm of UAVs based on GSA to detect unknown targets in unknown environments. Each UAV can communicate using long-range wireless communications. The challenging part of the system model is to successfully detect all of the targets in an unknown environment within a short period and with fewer iterations by the swarm. Initially, when the UAVs are deployed in the proposed GSA swarm-based UAV reconnaissance, they find the first target based on the searching strategy. Whenever any UAV within the swarm detects any target, that UAV broadcasts the target's location to the other UAVs within the swarm through a long-range communication system. Because UAVs are considered to be swarms, they can communicate and create strong connections with one another. A fitness function is calculated after the detection of the first target. The GSA-based tactics necessary for

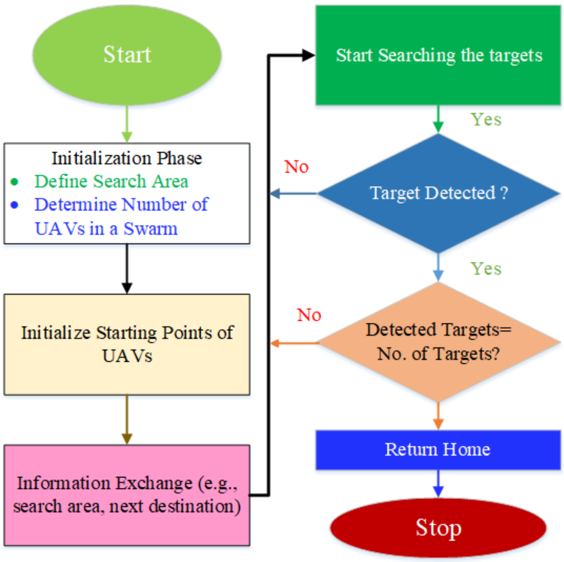


FIGURE 2. Flowchart of proposed GSA swarm-based UAV reconnaissance. (UAV swarm begins reconnaissance based on defined search area.)

performing this fitness function are discussed in the following section.

A flowchart of the proposed scheme demonstrates the working mechanism of the proposed GSA-based algorithm in FIGURE 2. The proposed search scheme consists of three major phases. The search area and the number of UAVs are determined in the first phase of the scheme. The swarm is formed in this part based on the GSA in an unknown environment with the total number of UAVs. Moreover, information about the search area, battery status, and detected target locations are exchanged among the UAVs of the swarm in this phase. The second phase shows the searching strategy in an unknown environment using the GSA and detects the location of the unknown targets, as shown in FIGURE 2. Finally, the search task and the return-to-base policy are determined after completing their surveillance of the entire area in the last phase. Table 2 presents the symbols and their descriptions as used in this paper.

A. GSA SWARM-BASED SEARCH STRATEGIES

Based on the GSA, the swarm of UAVs is formed. The swarm explores the whole search area independently. Moreover, each UAV inside the swarm is searching for the target within the search area corresponding to the swarm. A target is considered to be detected if any UAV in the swarm is able to catch it. The proposed scheme generates an initial total population of N masses or UAVs, with the position of each mass defined by the following equation as [22], [25], [26], and [30]:

$$X_i = (x_i^1, x_i^2, \ldots, x_i{}^d, \ldots, x_i{}^n), \tag{1}$$

where $i = \{1, 2, \ldots., N\}$ and N are the number of UAVs in different swarms in the case of the GSA swarm-based UAV reconnaissance scheme. The fitness of each UAV or mass is calculated by the following equation:

$$fit_i(iter) = (x_i(iter) - x_p(iter))^2, \tag{2}$$

where x_i represents the position of the UAV and x_p represents the position of the random destination point after the initial deployment. Assume that the targets are detected by the UAV sensor/camera. In the simulation case, whenever any target is in the range of a UAV in a swarm, it is encircled, as shown in FIGURE 4. And then that target is considered as a detected target [32].

TABLE 2. Symbols and their descriptions.

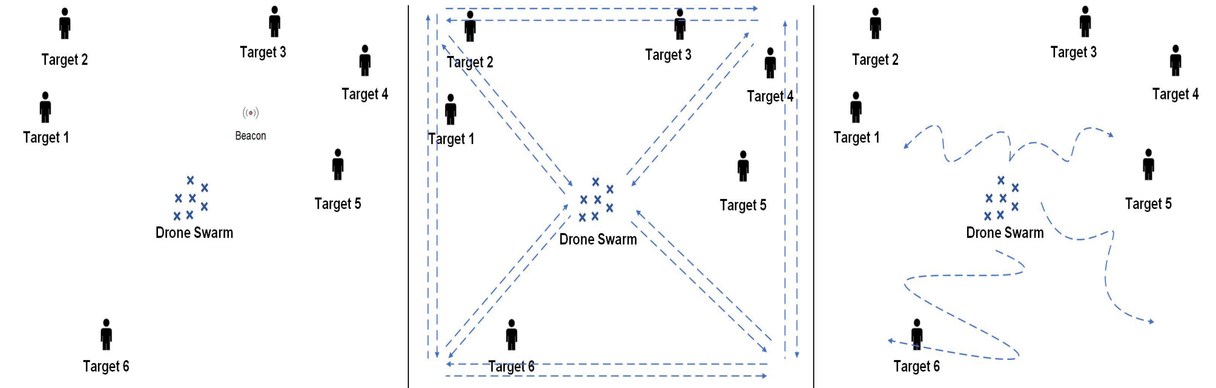
Symbol	Description
N	Total number of UAVs
x_i	Position of UAV
fit_i	Fitness of i^{th} UAV or mass
G	Gravitational constant
$best$	Best fitness
$worst$	Worst fitness
m_i	Gravitational Mass
M_i	Inertial Mass
v_i^d	Velocity of i^{th} UAV
a_i^d	Acceleration of i^{th} UAV
F_i^d	Force that acts on i^{th} UAV in dimension d
F_{ij}^d	Force acting on i^{th} UAV from j^{th} UAV
m_p	payload mass
r	lift-to-drag ratio
η	power transfer efficiency of the motor and propeller
p	power consumption of electronic circuit

1) BEACON-BASED GSA

A beacon-based GSA is proposed to consider a realistic scenario where information on the disaster/surveillance area is provided as a GPS position for UAV reconnaissance. In this search strategy, a single random position in the vicinity of the targets is given as a beacon signal, which in the real-time search can be considered as a highly compromised or high-priority disastrous area, as shown in FIGURE 3(a). The beacons are randomly generated in the area, and the targets are assumed to be in the vicinity of the beacons. It can be a single beacon in semi beacon-based strategy, and multiple beacons in a fully beacon-based strategy.

In the fully beacon-based strategy, each target has an associated beacon position. The beacon positions are assumed to be available with a high level of accuracy, corresponding to GPS coordinates. Specifically, we generate these positions randomly within a 100-meter square around the true target position for simulation purposes. This simulates the realistic uncertainty in GPS systems while maintaining proximity to the target. These beacon positions significantly influence the search process as they guide the swarm to focus on areas near the beacons, thereby limiting the exploration area and increasing efficiency.

In contrast, the semi-beacon-based strategy assumes only one beacon position is provided for all targets rather than



(a) Beacon-based GSA. (b) Pattern-based GSA. (c) Random search based GSA.

FIGURE 3. Different types of GSA based search techniques for unknown targets detection.

a dedicated beacon for each target. This single beacon acts as a starting reference for the swarm's search. Consequently, the swarm must explore a much larger area to detect targets, as the swarm does not have localized beacon information for each target. It increases the number of iterations required for target detection but allows for broader area coverage.

In the fully beacon-based strategy, the availability of accurate and localized beacon positions ensures that the swarm operates primarily near the beacons, reducing the search area and iterations required for target detection. This represents an ideal case where beacon positions provide precise guidance for the swarm.

In the semi-beacon-based strategy, the single beacon position serves as a general reference point. The swarm must subsequently rely on its search algorithms to cover the broader area systematically. This results in increased exploration and iterations but enables detection across the entire search area, demonstrating the system's adaptability in scenarios with limited beacon availability.

For the fully beacon-based strategy, the "random generation" of beacon positions refers to the simulation of GPS-like coordinates. Specifically, for each target, a random position is generated within a 100-meter square around the true target location. This square simulates the area of uncertainty typically associated with GPS readings, ensuring that the simulated beacon positions realistically reflect the variability of GPS accuracy.

For the semi-beacon-based strategy, the single beacon position is generated randomly within the search area. This single beacon serves as a fixed point for all targets, emphasizing the challenge of limited beacon availability and the need for robust search algorithms.

Instead of searching the whole area, the swarm directly goes towards the beacons and then explores the area around the beacon to detect the accurate position of the target, which is unknown. The fitness function for this scenario is:

$$fit_i(iter) = (x_i(iter) - x_b(iter))^2, \tag{3}$$

where x_i is the UAV position and x_b indicates the position of a beacon.

2) PATTERN-BASED GSA

For this scenario, the swarm searches the whole area randomly based on a pattern to minimize the search time. The random points are generated at the corners of the search area, as shown in FIGURE 3(b). The random position is updated once a target is detected. The fitness function for this scenario is:

$$fit_i(iter) = (x_i(iter) - x_n(iter))^2, \tag{4}$$

where x_n is the next destination position of a pattern-based GSA.

3) RANDOM SEARCH

In this case, the swarm searches the whole area, but the search is random. It does not follow any specific pattern and generates a random position at each destination point. Due to random behavior, it sometimes covers the whole area and sometimes leaves some targets undetected, as shown in FIGURE 3(c). In this case, the fitness function is given as:

$$fit_i(iter) = (x_i(iter) - x_q(iter))^2, \tag{5}$$

where x_q is the next random point.

After calculating the fitness function according to any of the above search strategies, the gravitational constant can be calculated as follows:

$$G(iter) = G_0 * e^{(-\beta * iter/iter_{max})}, \tag{6}$$

where G_0 is the value of the gravitational constant at the first iteration, $iter_{max}$ is the maximum number of iterations, and β is a constant ($\beta > 1$). The best and worst-case fitness values of each UAV are calculated using the following equations for the minimization problem:

$$best(iter) = minfit_j(iter), \tag{7}$$

$$worst(iter) = maxfit_j(iter), \tag{8}$$

where $j \in \{1, \ldots, N\}$. Moreover, the mass of i^{th} UAV is updated using (6) and (7)

$$m_i(iter) = \frac{fit_i(iter) - worst(iter)}{best(iter) - worst(iter)}, \tag{9}$$

$$M_i(iter) = \frac{m_i(iter)}{\sum_{j=1}^{N} m_j(iter)}, \tag{10}$$

where m_i represents the gravitational mass and M_i represents the inertial mass. The velocity of i^{th} UAV can be expressed as following equation [22], [25], [26], [30]:

$$v_i^d(iter+1) = rand_i {v_i}^d(iter) + a_i^d(iter), \tag{11}$$

where $rand_i$ returns a random number from the interval $\{0,1\}$. Moreover, the acceleration of mass i^{th} UAV (a_i^d) with the application force ${F_i}^d$ depends on its corresponding force (${F_i}^d$) and mass (M_i). The acceleration (${a_i}^d$) of i^{th} UAV can be expressed as follows:

$${a_i}^d(iter) = \frac{{F_i}^d(iter)}{M_i(iter)} \tag{12}$$

Here, it should be noted that the velocity and acceleration values depend on the search algorithm and can be distinct for two different algorithms at each iteration. Furthermore, the position (${x_i}^d$) of i^{th} UAV is updated using the following equation:

$$x_i^d(iter+1) = x_i(iter)^d + {v_i}^d(iter+1), \tag{13}$$

To give a stochastic characteristic to the GSA algorithm, it is considered that the total force ${F_i}^d$ acts on i^{th} UAV in dimension d. Where d is a randomly weighted sum of i^{th} components of the forces exerted by another UAV [22], [30]. Random weighting in the velocity update introduces stochasticity, which is critical for exploring unknown environments. The weighting ensures that UAVs do not converge prematurely, enhancing their ability to detect targets in complex search areas.

The performance comparison details of the strategies given above are discussed in the simulation results section.

V. SIMULATION RESULTS

This section analyzes the results of three cases for the proposed GSA swarm-based searching scheme and compares these results with existing algorithm-based searching schemes using MATLAB simulation. Table 3 lists the parameters that are used to conduct the simulation.

The total number of iterations and coverage area with respect to the number of iterations are analyzed. The following methods for detecting targets in an unknown environment are compared: DPSO, random search algorithm, and GSA swarm-based UAV reconnaissance methods. A 2D model is considered with some specified search area of 250×250. Moreover, the target detection process in an unknown 2D environment of the proposed scheme is shown in FIGURE 4. The other parameters $\eta = 0.5$, $m_p = 2$, $r = 3$, $p = 0.1$, $\beta = 2$, and $N = \{5, 7, 9\}$ are considered to allow a fair comparison of the proposed scheme with conventional search schemes [31].

TABLE 3. Simulation parameters.

Parameter	Values
Power Transfer Efficiency of the Motor and Propeller, (η)	0.5
Payload mass (m_p)	2
Lift to drag ratio (r)	3
Power Consumption of Electronic Circuit (p)	0.1
Total Number of UAVs (N)	5,7,9

A single swarm is first considered in an unknown environment for the GSA swarm-based UAV reconnaissance from the base (0,0). The initial exploration process by a swarm of UAVs using GSA swarm-based UAV reconnaissance is shown in FIGURE 4. The search environment is divided into an area of size 250×250, where the 1 square represents 0.1 km [21]. Three targets are placed in the area unknown to the swarm. Whenever a target is detected by any of the UAVs of the respective swarm within its search area, the detected targets are marked by larger circles, as shown in FIGURE 4. The swarm searched and detected the targets based on the GSA swarm-based UAV reconnaissance. All unknown targets are marked by stars, and the detected targets are marked by larger circles in FIGURE 4.

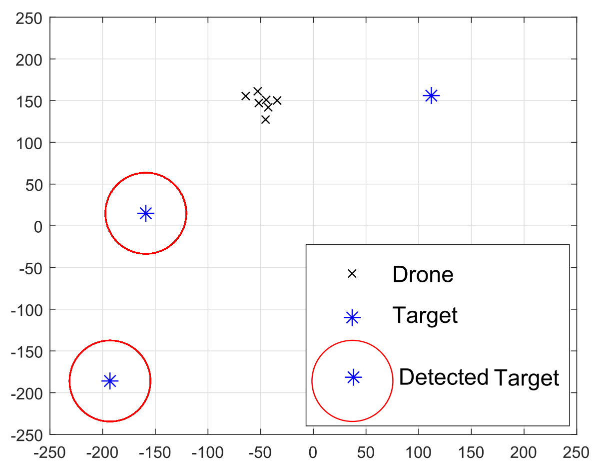


FIGURE 4. GSA swarm-based UAV reconnaissance for 250 × 250 area.

By utilizing the GSA swarm-based UAV reconnaissance, all targets are successfully detected by the swarm, as shown in FIGURE 4. The path traces of GSA swarm-based UAV reconnaissance strategies are shown in FIGURES 5-8. In FIGURE 5, three different path traces

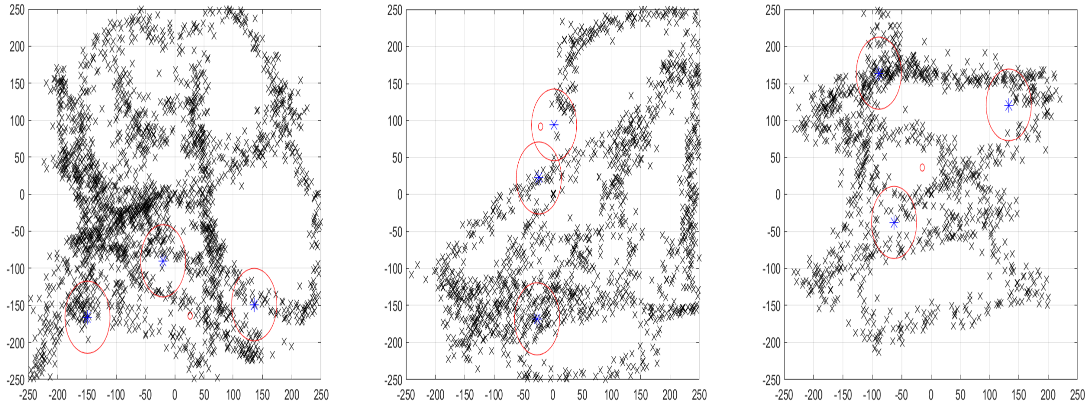


FIGURE 5. Semi Beacon-based GSA.

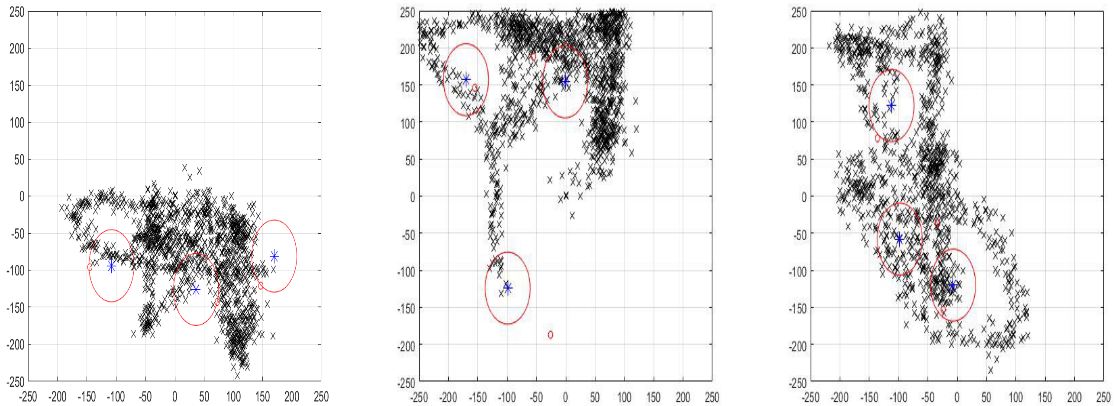


FIGURE 6. Fully Beacon-based GSA.

of semi-beacon-based GSA are shown where only a single beacon in a red circle can be seen, which helps in detecting the targets.

In FIGURE 6, a fully beacon-based GSA is shown with multiple beacons. The difference between semi-beacon-based and fully beacon-based path traces can be clearly observed. Fully beacon-based is the ideal case, and the swarm only visits the area near beacons. However, semi-beacon-based UAVs cover most of the search area and detect targets in more iterations than fully-beacon-based UAVs. In FIGURE 7, pattern-based search traces are shown, which do not have beacons but provide almost similar coverage and detect all the targets. Furthermore, the random search is shown in FIGURE 8, which sometimes takes a few iterations and sometimes takes much longer than the rest of the strategies. Therefore, the number of iterations with random search is higher than the other search strategies with less coverage, leaving some of the targets undetected.

FIGURE 9, 10, and 11 show the iteration comparisons for the proposed GSA swarm-based UAV reconnaissance operating in an area of 250 × 250 (for $N = 7$). The proposed scheme required less time to detect the targets in an unknown environment because the GSA algorithm required fewer iterations than other algorithms. FIGURE 9 compares the number of iterations required by various search algorithms to locate targets in a 250 × 250 area. The fully beacon-based GSA consistently demonstrates the lowest number of iterations across all scenarios, showcasing its efficiency in convergence. The semi-beacon-based GSA and pattern-based GSA perform moderately well, but their iteration counts increase notably with additional targets, indicating slightly slower adaptability. On the other hand, random search exhibits the highest iteration counts, particularly for three targets. It requires almost 67% more iterations, reflecting its inefficiency due to the absence of guided exploration.

Moreover, FIGURE 10 illustrates that the number of iterations varies due to the different numbers of UAVs in the proposed beacon-based scheme. According to the GSA algorithm, a higher number of UAVs in a swarm takes fewer iterations to detect all the targets successfully in an unknown environment. Hence, the higher number of UAVs in the GSA-based swarm provides fewer iterations than a lower number of UAVs.

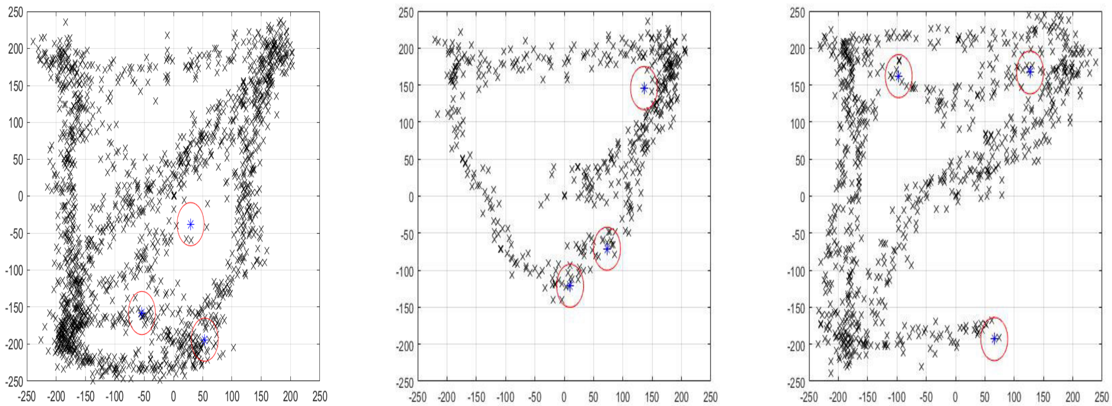


FIGURE 7. Pattern-based GSA.

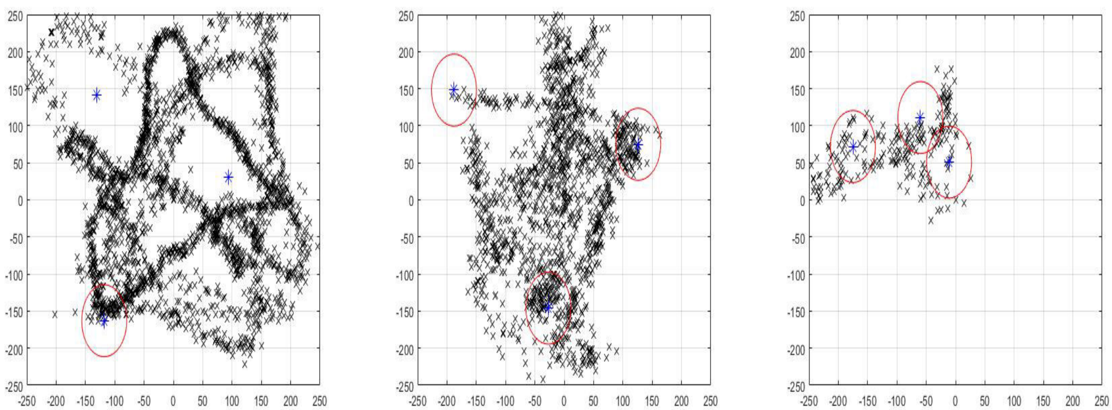


FIGURE 8. Random search.

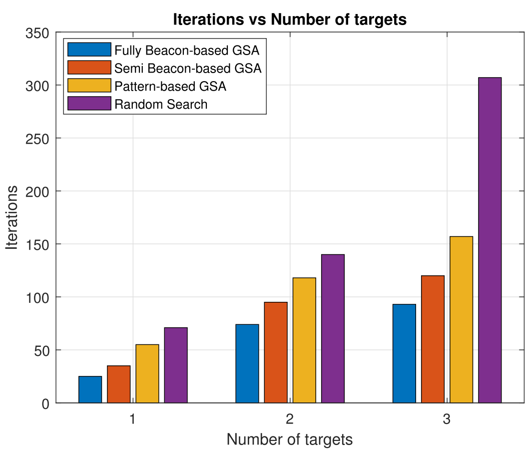


FIGURE 9. Comparison of number of iterations for an area sized 250 × 250.

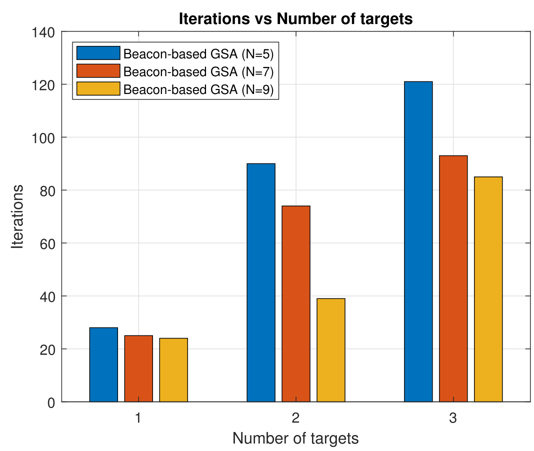


FIGURE 10. Comparison of number of UAVs in a swarm w.r.t. number of iterations for an area sized 250 × 250.

Furthermore, FIGURE 11 compares the number of iterations required for different search areas, namely 100 × 100, 250 × 250, and 500 × 500. The results demonstrate that the proposed GSA swarm beacon-based UAV reconnaissance schemes achieve maximum coverage across varying search areas, successfully detecting all targets while requiring fewer iterations compared to other schemes.

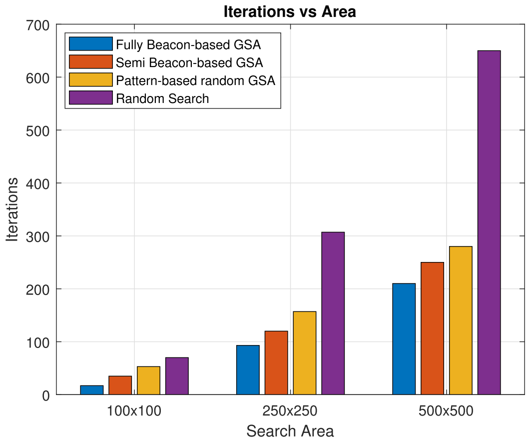


FIGURE 11. Comparison of coverage area with respect to number of iterations for different search areas.

The fully beacon-based GSA outperforms other methods, requiring the fewest iterations across all search areas. As the search area increases, the iteration counts for all methods rise, but the Fully Beacon-based GSA maintains its efficiency. The semi-beacon-based GSA and pattern-based random GSA exhibit moderate performance, with their iteration counts increasing significantly in larger areas. Random search is the least efficient, especially for the 500×500 region; it requires almost 70% more iterations than fully beacon-based GSA.

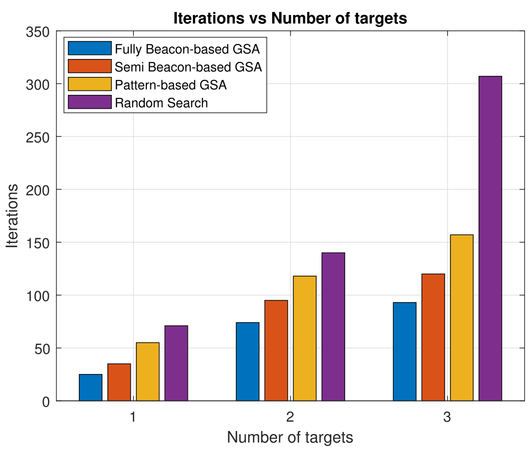


FIGURE 12. Comparison of the proposed GSA with existing search techniques.

Lastly, the comparison of the proposed GSA with the existing search strategies shows its effectiveness over the hybrid, DPSO, and random search techniques in FIGURE 12.

VI. CONCLUSION

This paper presents a GSA swarm-based UAV reconnaissance scheme for multiple target detections in an unknown environment. The performance of the proposed scheme is analyzed in terms of the number of iterations and coverage area and compared with the other conventional UAV reconnaissance schemes. Additionally, different GSA-based search strategies are developed to investigate the performance of the proposed scheme. The simulation results show that the proposed GSA swarm-based UAV reconnaissance scheme requires significantly less search time and fewer iterations than the DPSO and random search-based UAV reconnaissance schemes to detect targets successfully in an unknown environment. Moreover, the proposed scheme requires significantly fewer iterations for maximum coverage than the other schemes to detect targets in an unknown environment.

In the current work, the authors have implemented and analyzed a GSA swarm-based UAV reconnaissance scheme in a two-dimensional (2D) environment. This is chosen as an initial step to validate the feasibility, effectiveness, and efficiency of this algorithm under controlled conditions. Real-world UAV operations often occur in three-dimensional (3D) spaces, where vertical movement is critical in expanding the search area and improving target detection capabilities. The authors intend to extend the work to 3D environments in future research. Moreover, developing advanced obstacle avoidance strategies using sensor integration and real-time environmental mapping can enhance the reliability of the GSA-based UAV reconnaissance system in more complex and dynamic environments. Furthermore, obstacle detection while searching for the UAV's target can be considered a future work of this paper. Combining GSA with other metaheuristic algorithms, such as genetic algorithms or ant colony optimization, could lead to improved performance in terms of search efficiency and computational cost.

REFERENCES

[1] T. R. Beegum, M. Y. I. Idris, M. N. B. Ayub, and H. A. Shehadeh, "Optimized routing of UAVs using bio-inspired algorithm in FANET: A systematic review," *IEEE Access*, vol. 11, pp. 15588–15622, 2023, doi: 10.1109/ACCESS.2023.3244067.

[2] M. Masuduzzaman, T. Rahim, A. Islam, and S. Y. Shin, "UxV-based deep-learning-integrated automated and secure garbage management scheme using blockchain," *IEEE Internet Things J.*, vol. 10, no. 8, pp. 6779–6793, Apr. 2023, doi: 10.1109/JIOT.2022.3156617.

[3] M. Alhafnawi, H. A. B. Salameh, A. Masadeh, H. Al-Obiedollah, M. Ayyash, R. El-Khazali, and H. Elgala, "A survey of indoor and outdoor UAV-based target tracking systems: Current status, challenges, technologies, and future directions," *IEEE Access*, vol. 11, pp. 68324–68339, 2023, doi: 10.1109/ACCESS.2023.3292302.

[4] M. Masuduzzaman, A. Islam, K. Sadia, and S. Y. Shin, "UAV-based MEC-assisted automated traffic management scheme using blockchain," *Future Gener. Comput. Syst.*, vol. 134, pp. 256–270, Sep. 2022.

[5] S. Javaid, N. Saeed, Z. Qadir, H. Fahim, B. He, H. Song, and M. Bilal, "Communication and control in collaborative UAVs: Recent advances and future trends," *IEEE Trans. Intell. Transp. Syst.*, vol. 24, no. 6, pp. 5719–5739, Jun. 2023, doi: 10.1109/TITS.2023.3248841.

[6] K. Kuru, "Planning the future of smart cities with swarms of fully autonomous unmanned aerial vehicles using a novel framework," *IEEE Access*, vol. 9, pp. 6571–6595, 2021, doi: 10.1109/ACCESS.2020.3049094.

[7] T. M. Shami, A. A. El-Saleh, M. Alswaitti, Q. Al-Tashi, M. A. Summakieh, and S. Mirjalili, "Particle swarm optimization: A comprehensive survey," *IEEE Access*, vol. 10, pp. 10031–10061, 2022, doi: 10.1109/ACCESS.2022.3142859.

[8] S. Gao, J. Wu, and J. Ai, "Multi-UAV reconnaissance task allocation for heterogeneous targets using grouping ant colony optimization algorithm," *Soft Comput.*, vol. 25, no. 10, pp. 7155–7167, May 2021.

[9] A. Beghriche, A. Kout, and A. Abed, "A bio-inspired energy-efficient routing protocol based on penguins search optimization for FANETs," in *Proc. 1st Int. Conf. Comput. Commun. Intell. Syst.*, Jijel, Algeria, Nov. 2022, pp. 128–133, doi: 10.1109/I3CIS56626.2022.10076126.

[10] G. P. Kladis, L. Doitsidis, and N. C. Tsourveloudis, "Energy-efficient path-planning for UAV swarm based missions: A genetic algorithm approach," in *Proc. Int. Conf. Unmanned Aircr. Syst. (ICUAS)*, Jun. 2024, pp. 458–463.

[11] J. Lansky, A. M. Rahmani, M. H. Malik, E. Yousefpoor, M. S. Yousefpoor, M. U. Khan, and M. Hosseinzadeh, "An energy-aware routing method using firefly algorithm for flying ad hoc networks," *Sci. Rep.*, vol. 13, no. 1, p. 1323, Jan. 2023.

[12] S. Ghosh and P. Kuila, "Efficient offloading in disaster-affected areas using unmanned aerial vehicle-assisted mobile edge computing: A gravitational search algorithm-based approach," *Int. J. Disaster Risk Reduction*, vol. 97, Oct. 2023, Art. no. 104067.

[13] Y. Zhou, B. Rao, and W. Wang, "UAV swarm intelligence: Recent advances and future trends," *IEEE Access*, vol. 8, pp. 183856–183878, 2020, doi: 10.1109/ACCESS.2020.3028865.

[14] M. R. Brust, M. Zurad, L. Hentges, L. Gomes, G. Danoy, and P. Bouvry, "Target tracking optimization of UAV swarms based on dual-pheromone clustering," in *Proc. 3rd IEEE Int. Conf. Cybern. (CYBCONF)*, Exeter, U.K., Jun. 2017, pp. 1–8, doi: 10.1109/CYBCONF.2017.7985815.

[15] I.-K. Ha and Y.-Z. Cho, "A probabilistic target search algorithm based on hierarchical collaboration for improving rapidity of drones," *Sensors*, vol. 18, no. 8, p. 2535, Aug. 2018.

[16] W. Weihua, W. Peizao, and N. Zhaodong, "A real-time detection algorithm for unmanned aerial vehicle target in infrared search system," in *Proc. IEEE Int. Conf. Signal Process., Commun. Comput. (ICSPCC)*, Qingdao, China, Sep. 2018, pp. 1–5, doi: 10.1109/ICSPCC.2018.8567718.

[17] P. Wang, W. Wang, and H. Wang, "Infrared unmanned aerial vehicle targets detection based on multi-scale filtering and feature fusion," in *Proc. 3rd IEEE Int. Conf. Comput. Commun. (ICCC)*, Chengdu, China, Dec. 2017, pp. 1746–1750, doi: 10.1109/COMPCOMM.2017.8322839.

[18] L. Hong, Y. Wang, Y. Du, X. Chen, and Y. Zheng, "UAV search-and-rescue planning using an adaptive memetic algorithm," *Frontiers Inf. Technol. Electron. Eng.*, vol. 22, no. 11, pp. 1477–1491, Nov. 2021.

[19] M. R. Usman, M. A. Usman, M. A. Yaq, and S. Y. Shin, "UAV reconnaissance using bio-inspired algorithms: Joint PSO and penguin search optimization algorithm (PeSOA) attributes," in *Proc. 16th IEEE Annu. Consum. Commun. Netw. Conf. (CCNC)*, Las Vegas, NV, USA, Jan. 2019, pp. 1–6, doi: 10.1109/CCNC.2019.8651831.

[20] Y. Cai and S. X. Yang, "A potential field-based PSO approach for cooperative target searching of multi-robots," in *Proc. 11th World Congr. Intell. Control Autom.*, Jun. 2014, pp. 1029–1034.

[21] S. Li, L. Li, G. Lee, and H. Zhang, "A hybrid search algorithm for swarm robots searching in an unknown environment," *PLoS ONE*, vol. 9, no. 11, Nov. 2014, Art. no. e111970, doi: 10.1371/journal.pone.0111970.

[22] X. Zhang and M. Ali, "A bean optimization-based cooperation method for target searching by swarm UAVs in unknown environments," *IEEE Access*, vol. 8, pp. 43850–43862, 2020, doi: 10.1109/ACCESS.2020.2977499.

[23] S. Lee, S. Lee, and H. Kim, "Differential security barriers for virtual emotion detection in maritime transportation stations with cooperative mobile robots and UAVs," *IEEE Trans. Intell. Transp. Syst.*, vol. 24, no. 2, pp. 2461–2471, Feb. 2023, doi: 10.1109/TITS.2022.3172668.

[24] E. Rashedi, E. Rashedi, and H. Nezamabadi-Pour, "A comprehensive survey on gravitational search algorithm," *Swarm Evol. Comput.*, vol. 41, pp. 141–158, Aug. 2018.

[25] A. Hashemi, M. B. Dowlatshahi, and H. Nezamabadi-Pour, "Gravitational search algorithm: Theory, literature review, and applications," in *Handbook of AI-based Metaheuristics*. CRC Press, 2021, pp. 119–150.

[26] H. Mittal, A. Tripathi, A. C. Pandey, and R. Pal, "Gravitational search algorithm: A comprehensive analysis of recent variants," *Multimedia Tools Appl.*, vol. 80, no. 5, pp. 7581–7608, Feb. 2021.

[27] X. Liu and Z. Zhang, "A vision-based target detection, tracking, and positioning algorithm for unmanned aerial vehicle," *Wireless Commun. Mobile Comput.*, vol. 2021, no. 1, Jan. 2021, Art. no. 5565589.

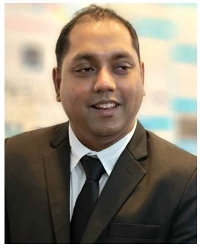
[28] X. Zhao, R. Yang, Y. Zhang, M. Yan, and L. Yue, "Deep reinforcement learning for intelligent dual-UAV reconnaissance mission planning," *Electronics*, vol. 11, no. 13, p. 2031, Jun. 2022.

[29] W. Minghua, Z. Yingzhuo, Z. Longgang, and G. Xusheng, "Rough set neural network evaluation method for UAV reconnaissance effectiveness," in *Proc. IEEE Int. Conf. Adv. Electr. Eng. Comput. Appl. (AEECA)*, Dalian, China, Aug. 2022, pp. 460–464, doi: 10.1109/AEECA55500.2022.9918924.

[30] H. Xu, S. Jiang, and A. Zhang, "Path planning for unmanned aerial vehicle using a mix-strategy-based gravitational search algorithm," *IEEE Access*, vol. 9, pp. 57033–57045, 2021, doi: 10.1109/ACCESS.2021.3072796.

[31] R. D'Andrea, "Guest editorial can drones deliver?" *IEEE Trans. Autom. Sci. Eng.*, vol. 11, no. 3, pp. 647–648, Jul. 2014, doi: 10.1109/TASE.2014.2326952.

[32] J. N. Yasin, S. A. S. Mohamed, M.-H. Haghbayan, J. Heikkonen, H. Tenhunen, and J. Plosila, "Unmanned aerial vehicles (UAVs): Collision avoidance systems and approaches," *IEEE Access*, vol. 8, pp. 105139–105155, 2020, doi: 10.1109/ACCESS.2020.3000064.



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