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Unmanned aerial vehicle path planning in a 3D environment using a hybrid algorithm

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ABSTRACT

The optimal unmanned aerial vehicle (UAV) path planning using bio-inspired algorithms requires high computation and low convergence in a complex 3D environment. To solve this problem, a hybrid A*-FPA algorithm was proposed that combines the A* algorithm with a flower pollination algorithm (FPA). The main idea of this algorithm is to balance the high speed of the A* exploration ability with the FPA exploitation ability to find an optimal 3D UAV path. At first, the algorithm starts by finding the locally optimal path based on a grid map, and the result is a set of path nodes. The algorithm will select three discovered nodes and set the FPA's initial population. Finally, the FPA is applied to obtain the optimal path. The proposed algorithm's performance was compared with the A*, FPA, genetic algorithm (GA), and partical swarm optimization (PSO) algorithms, where the comparison is done based on four factors: the best path, mean path, standard deviation, and worst path length. The simulation results showed that the proposed algorithm outperformed all previously mentioned algorithms in finding the optimal path in all scenarios, significantly improving the best path length and mean path length of 79.3% and 147.8%, respectively.

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1. INTRODUCTION

Unmanned aerial vehicles (UAVs) are widely used and important in our lives because of their ability to operate in challenging and dangerous areas, particularly in the military and industrial sectors. Planning a route from a starting point to a target location while avoiding environmental obstacles is critical to the mission's success [1], [2]. Path planning is generally divided into two types: when the environment is known, path planning is said to be offline, and when it can adjust a path in reaction to environmental changes, it is said to be online [3], [4].

On the other hand, five categories have been established for UAV 3D route planning algorithms. Each category differs from the others in terms of compatibility with specific characteristics [1]–[5]. The first category is node-based algorithms, including the A*, dijkstra algorithms [6], [7], and the D-star algorithm [8]. The second type of algorithm is sample-based, such as the rapidly exploring random tree (RRT) algorithm [9], probabilistic road maps (PRM) [10], and others. The third category is based on a mathematical model [5], [11]. The fourth type is bio-inspired algorithms, including fuzzy logic (FL) [12], the improved artificial bee colony (IABC) algorithm [13], genetic algorithm (GA) [14], [15], the improved ant colony optimization (IACO) [16], particle swarm optimization (PSO) [17], flower pollination algorithm (FPA) [18], and modified particle swarm optimization (MPSO) [3]. The fifth category is multi-fusion-based algorithms, which combine two or more algorithms; these algorithms seek to solve and enhance route planning problems by increasing their quality, stability, and convergence performance [19]. Examples include a probabilistic roadmap based on ant colony optimization [20], improved particle swarm optimization (IPSO), grey wolf optimizer (GWO) [19], a hybrid flower pollination and genetic algorithm (FPA-GA) [21], (BAS-GA) is a combination of the genetic algorithm and the beetle antennae search algorithm [22], and others. Depending on the situation, each of these algorithms has advantages and disadvantages. These algorithms, in particular, look for the shortest route length, minimize the overall time, and avoid obstacles.

Many researchers have used various techniques to generate global path planning with obstacle avoidance. The researchers combined the third-order B-spline curve, ACO, and PRM in a 2D environment [20]. This strategy can find a smooth, straight path but has not been tested in 3D environments. While the authors in [6], depending on the chosen nodes, used both the A* and dijkstra algorithms in a realistic 3D environment. The selected route was not smooth, and the procedure did not find the optimal one. Athira *et al.* [23] used an improved artificial potential field (APF) technique with a sampling-based bidirectional RRT algorithm to create an offline route plan. This approach combines two local route planning algorithms; hence, it cannot determine the ideal path between the beginning and goal places. In paper [24], [25] improved global path-planning systems were constructed using the A* algorithm paired with the ACO and GA. They covered a 2D situation only; a 3D scenario was not addressed. A hybrid approach [26] is suggested that combines the grasshopper optimization algorithm (GOA) with an improved multinomial logistic regression algorithm.

Furthermore, Alabdalbari and Abed [27] proposed a hybrid gray wolf-particle swarm optimization (HGWO-PSO). Both hybridization algorithms increased the range of choices and assisted in avoiding stagnation in 2D environments. While Zhao *et al.* [28] used PSO and improved whale optimization (IWOA) to quicken convergence, it proposed combining improved whale optimization and particle swarm optimization (IWOA-PSO). After using an IWOA to prevent the system from settling at the local optimum, they used the crossover technique for information exchange. The author did not consider the minimum path length while determining the best route, which resulted in high energy usage for the required operation.

From previous studies, A* is the preferred route planning approach out of all the options mentioned above due to its ease of use. The shortest local route will always be found using the A* approach on graphs; however, it cannot find the optimal path in a continuous environment. On the other hand, bio-inspired algorithms have high computational complexity and low convergence. In this study, we proposed to use the hybrid algorithm of A* and FPA to find the optimal 3D path of the UAV in a realistic, continuous environment with reduced computational complexity by balancing exploration and exploitation processes by exploiting the A* exploration ability, and the FPA exploitation ability and then employing the B-splines algorithm to smooth the path.

The paper is organized as follows: the issue formulations of quadcopter path planning, the A*, FPA, and A*-FPA approaches, are described in section 2, which maps A*-FPA to quadcopter path planning, and section 3 describe outlines the underlying principles of the recommended environmental model and the B-spline method. The results of numerous well-designed, related simulations are provided and thoroughly discussed in section 4. In section 5, a conclusion is reached.

2. THE PROPOSED A*- FPA ALGORITHM

This section describes the A* and FPA algorithms' principal operations are then detailed. Finally, a description of the hybrid A*-FPA algorithm's use in determining the best route planning.

2.1. The principal work of A*

The A* algorithm is a heuristic search route that performs many calculations when determining the node state and choosing the lowest cost. The A* algorithm offers the benefits of fast search and easy operation while planning a large environment, and the resulting route comprises several straight-line segments. Implementing a more advanced A* algorithm does 3D path planning, as shown in Figure 1. By optimizing the heuristic function, the A* method meets the acceptance requirement and is more suitable for the 3D environment. The heuristic cost of the A* method is described by the estimated function f(n) [6], [8], [29]:

$$f(n) = h(n) + g(n) \tag{1}$$

$$h(n) = \sqrt{(g_x - n_x)^2 + (g_y - n_y)^2 + (g_z - n_z)^2} \tag{2}$$

$$g(n) = \sqrt{(n_x - s_x)^2 + (n_y - s_y)^2 + (n_z - s_z)^2} \tag{3}$$

Where the least cost from the starting node to the current node (n) is represented by $g(n)$. The least cost between the current node and the goal node is $h(n)$, the current node's coordinates are n_x, n_y, and n_z, the target node's coordinates are g_x, g_y, and g_z, and the starting nodes' coordinates are s_x, s_y, and s_z.

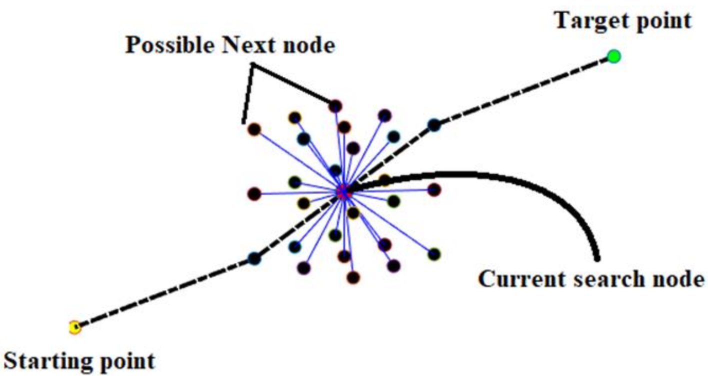


Figure 1. A* algorithm work in a 3D environment

2.2. The principal work of FPA

Yang in 2012 [30] developed the FPA, a nature-inspired population-based algorithm. Flower pollination ensures that plants reproduce as efficiently as possible by surviving the finest flowers among flower plants. A flower's principal function is reproduction via pollination. Pollen transport is typically associated with flower pollination, and insects, birds, insects, and other animals are frequently involved [30], [31].

Abiotic and biotic pollination are the two primary varieties. Biotic pollination involves pollen transmission by pollinators such as insects and animals and is used by around 90% of flowering plants. Around 10% of pollination is accomplished by abiotic pollination, which does not need pollinators. On the other hand, there are two ways to pollinate plants: cross-pollination and self-pollination. Self-pollination occurs when pollen from the same flower or several flowers of the same plant is used to populate a single flower, as opposed to cross-pollination, which occurs when pollen from a flower of a different plant is used to nourish a single flower. The researchers in [30], [31] created the following rules to serve as a model for the FPA:

a. During biotic cross-pollination, a kind of global pollination, pollinators use levy flights to move pollen from one plant to another. For the significant steps, this distribution is appropriate (s "s_0>0).

$$A_i^{T+1} = A_i^T + L(g_{best} - A_i^T) \tag{4}$$

$$L = \frac{\lambda\Gamma(\lambda)\times\sin\left(\frac{\pi\lambda}{2}\right)}{\pi\times s^{1+\lambda}}, \quad (|s| \rightarrow \infty) \tag{5}$$

b. Abiotic self-pollination is recognized as local pollination.

$$A_i^{T+1} = A_i^T + \epsilon(A_j^T - A_k^T) \tag{6}$$

Where A_i is the variable solution, g_{best} s the best-found solution, T is the number of iterations, ϵ is the random number, ϵ [0,1], $\Gamma(\lambda)$ is the general gamma function, s_0 is a minimal step, and (A_j^T *and* A_k^T) are members of the same plant species (chosen arbitrarily from the same population). This study will employ λ=1.5, as Yang [30] suggested, as the scaling parameter to control the step size.

c. It is assumed that flower constancy represents the probability of reproduction.

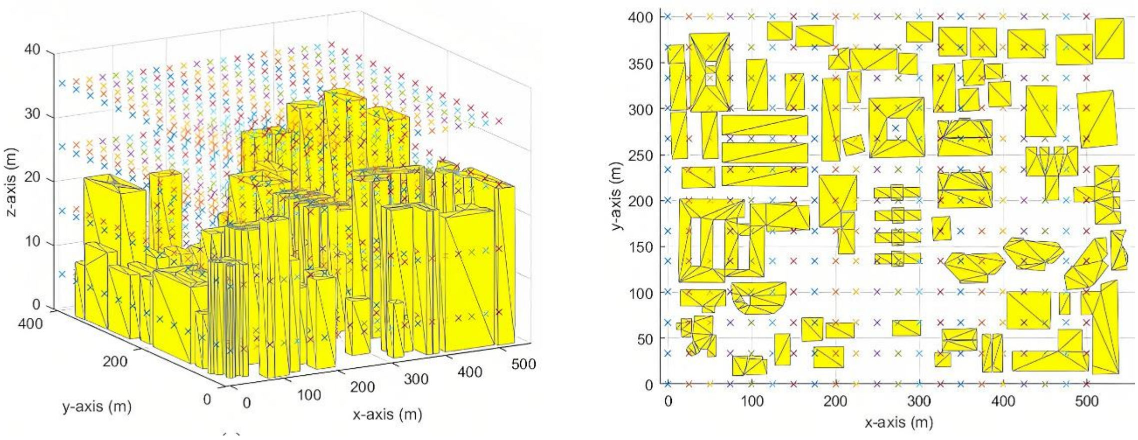
d. A probability switch (ρ) is proposed to control the amount of local and global pollination.

2.3. Proposed hybrid A*-FPA algorithm

The hybrid A*-FPA algorithm will be proposed to address the problem of finding the UAV path planning, avoiding collisions with high computational requirements, avoiding the algorithm falling into local optimal, and modifying the FPA search space to prevent the algorithm from searching in an insufficient area. The proposed algorithm begins by defining four layers of nodes, each having 22*13 nodes, as illustrated in Figures 2(a) and (b). Then the A* technique will be used to determine the optimal route from the identified nodes and define them as a node sequence. Due to the large number of nodes that can be chosen depending on the distance between the starting and target nodes, the path length can increase. The best three nodes from each node will be chosen to reduce the path length and streamline the computational process, and they will form the initial population of the FPA. From a distance between the nodes in one layer and the best global solution, the search space will be improved as follows for each axis:

$$Upper\ band = g_{best} + distance\ between\ two\ grid\ nodes/2 \tag{7}$$

$$Lower\ band = g_{best} - distance\ between\ two\ grid\ nodes/2 \tag{8}$$



(a) (b)

Figure 2. The grid nodes distribution on the environment; (a) 3D view and (b) top view

The FPA is then considered to find the optimal path by minimizing the cost function, as shown in (9) and (10). To ensure a safe path, the punishment value (P_o) is added to the cost function. The suggested method as a whole may be articulated in Figure 3 (in Appendix).

$$cost = Path\ length\ + P_o \tag{9}$$

$$Path\ length = \sqrt{(x_{l+1} - x_l)^2 + (y_{l+1} - y_l)^2 (z_{l+1} - z_l)^2} \tag{10}$$

where the current node's coordinates are (x_l, y_l, z_l) and the next node's coordinates are $(x_{l+1}, y_{l+1}, z_{l+1})$.

3. METHOD

3.1. Environment design

Choose the shortest UAV path based on the delivery system between the beginning and destination points in a vast, static, and realistic area. We decided to use the University of Technology, Baghdad, Iraq (UOT) map for this study because of the diversity of building types and the areas with modern buildings. We created a map of the 560×410 m (229600 m^2) area using the website (https://cadmapper.com), a virtual 3D mapping library that served as a platform for urban construction and architectural activities. Using the 3D CAD tool autoCAD, as seen in Figure 4. The environment is downloaded as a DXF file, which autoCAD can access. It is then modified and transformed into an STL file for MATLAB use [6], [21].

3.2. B-spline algorithm

The most common path-planning method produces segments of straight lines. The discontinuity problem, mechanical wear, localization mistake, and slipping make paths with straight-line segments unsuitable [20]. Splines are often used as piecewise polynomial functions to approximate functions, curves, and surfaces or to interpolate collections of data points. A method for computing splines that is very effective was based on so-called B-splines [32]. The B-splines show how to create a general spline by linearly combining the appropriate number of basis functions. Where the N control points p_q (q=0, 1… N) and the r order of the B-spline curve as explained in (7) [20], [32].

$$p(t) = \sum_q^N p_q B_q^r(t) \qquad t_{r+1} \le t \le t_{N+1} \tag{11}$$

where $B_q^r(t)$ is B-spline basis function and the knot vector's r order specified as $(t_0,\ t_1, \dots,\ t_{N+r})$.

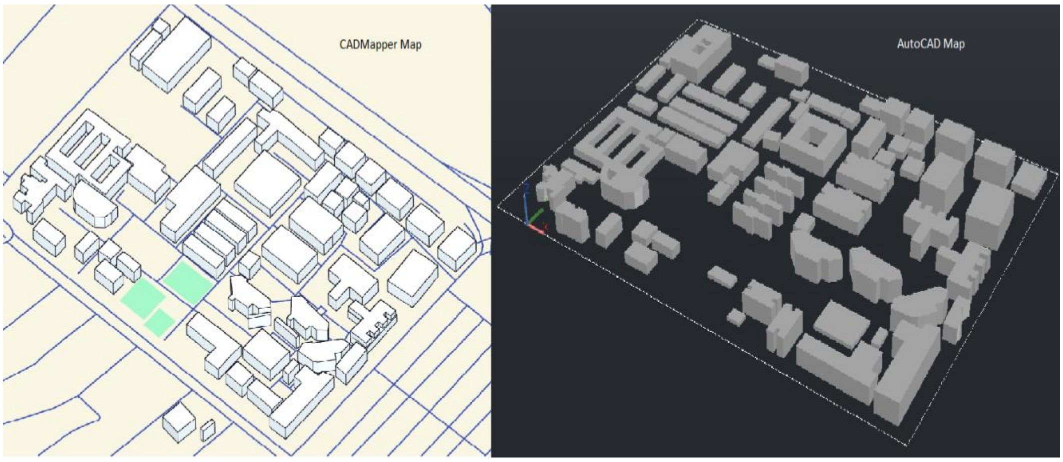


Figure 4. The UOT environment design at both CAD mapper and autoCAD environments

Can be calculated the B-spline basis function from the following recursive:

$$B_q^0(t) = \begin{cases} 1 & t_q \leq t \leq t_{q+1} \\ 0 & otherwise \end{cases} \tag{12}$$

$$B_q^r(t) = \frac{t-t_q}{t_{q+r}-t_q} B_q^{r-1}(t) + \frac{t_{q+r+1}-t}{t_{q+r+1}-t_{q+1}} B_{q+1}^{r-1} \quad r > 0 \tag{13}$$

$$t_q = \begin{cases} 0 & q < r \\ 1+q-r & r \leq q \leq N \\ 2+N-r & q > N \end{cases} \tag{14}$$

4. RESULTS AND DISCUSSION

With the suggested A*-FPA algorithms, the offline route planner can be evaluated between the beginning and goal points. Next, we will compare the performance to that of the FPA, A*, GA, and PSO algorithms. To cover all feasible situations with varying degrees of complexity and evaluate the method's performance in terms of best route length, mean route length, standard deviation, and worst value. Three distinct scenarios will be examined in the same realistic setting. Ten runs are performed for each scenario to test the method's robustness and its route length conclusions due to the meta-heuristic methods' random nature. Table 1 lists the parameters of the hybrid algorithms. Due to the complexity of UAV operations, each of these situations differs from the others. Table 2 explains each scenario's beginning location and target point. The simulations are run in MATLAB (R2016a) on a Windows 10 PC equipped with an Intel(R) Core (TM) i7-1165G7 processor running at 2.80 GHz and 8 GB of RAM.

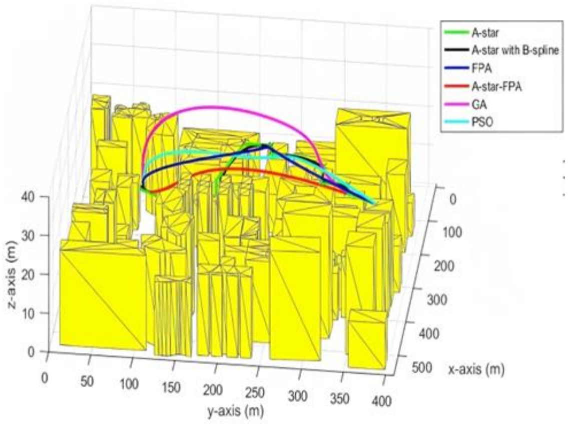
Table 1. A*-FPA algorithm parameters value

No.	Parameter name	Values
1	Population size (N)	40
2	Number of generations (T)	50
3	Number of variables	9
4	Switch probability (ρ)	0.2
5	Number of neighbor nodes	26
6	Number of trails	10

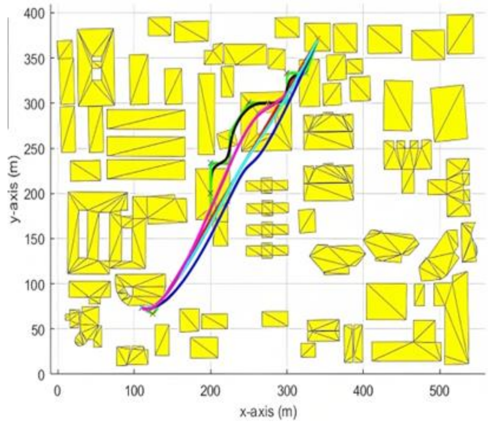
Table 2. The scenarios description for UAV travels

Scenario no.	Starting point	Target point
1	(110,73,0)	(340, 370, 19.5)
2	(110,73,0)	(495, 150, 0)
3	(50,330,0)	(272,278,0)

The results show that the hybrid algorithm finds the optimal 3D UAV path in various scenarios. In contrast, in the first scenario, the A* algorithm determines the best route based on the grid nodes. The found path using A* passes through 16 nodes, including the starting and target nodes, and the generated path avoided the obstacles with a length of 467.385 m. The B-spline algorithm smoothed this path, reducing the path length to 413.009 m. The FPA, GA, and PSO algorithms found the UAV safe path with lengths of 386.205 m, 391.688 m, and 382.283 m, respectively. While the proposed A*-FPA algorithm determines the optimal value, its length is 380.130 m, as shown in Figures 5(a), (b), and 6. On the other hand, the proposed algorithm is superior to the other algorithms in the mean value, standard deviation, and worst value, as explained in Table 3.



(a)



(b)

Figure 5. The UAV path determines in the first scenario in; (a) 3D view and (b) top view

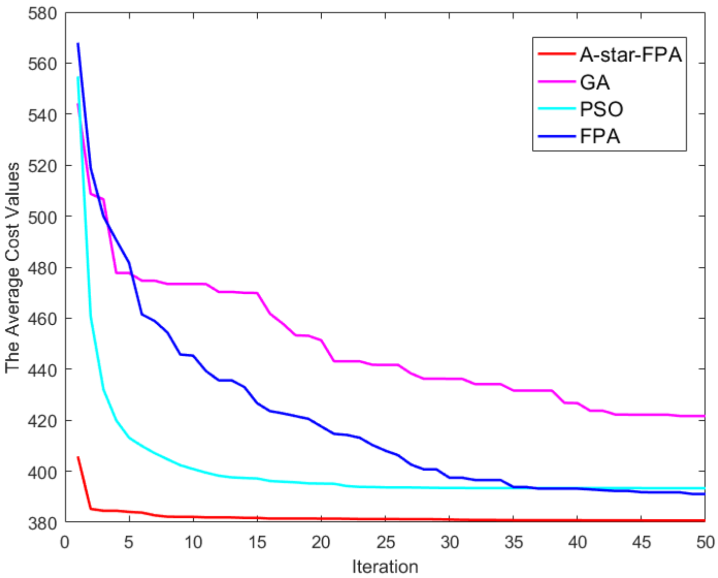
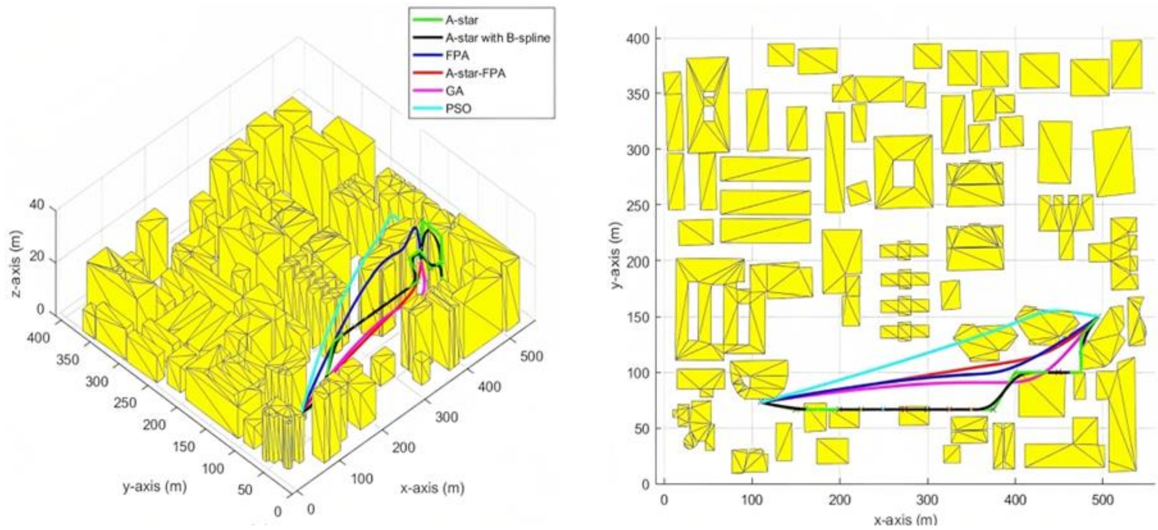


Figure 6. The algorithm's performance in the first scenario

In the second scenario, these algorithms found safe 3D UAV paths of different lengths. The A* algorithm found a path that passes through 19 grid nodes with a 486.501 m path length; after that, it is smoothed to reduce the length to 449.83 m. For meta-heuristic algorithms, the proposed hybrid algorithm is to determine the optimal path with a length equal to 396.192 m, which is superior to other algorithms, as shown in Figures 7(a), (b), and 8, where the path lengths for FPA, GA, and PSO are 403.803 m, 405.139 m, and 401.828 m, respectively.

Table 3. Path planning results in various scenarios

Scenario no.	Items	A*	FPA	GA	PSO	A*-FPA
1	Best	413.009	386.205	391.688	382.283	380.130
	Mean	-	391.079	421.631	393.382	380.688
	Std.	-	3.824	12.892	21.011	0.337
	Worst	-	397.911	437.954	452.071	381.144
2	Best	449.830	403.803	405.139	401.828	396.192
	Mean	-	409.001	416.526	415.239	396.509
	Std.	-	4.332	7.917	25.390	0.220
	Worst	-	415.378	431.546	482.273	396.931
3	Best	285.341	437.170	428.810	452.189	251.536
	Mean	-	525.603	604.110	657.160	253.306
	Std.	-	109.781	126.504	132.462	1.584
	Worst	-	733.456	772.211	764.794	256.387



(a) (b)

Figure 7. The UAV path planning in the second scenario is in; (a) 3D view and (b) top view

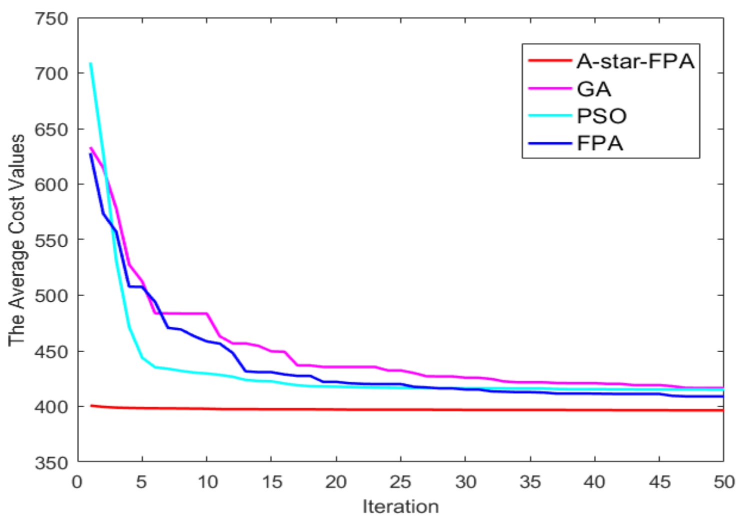
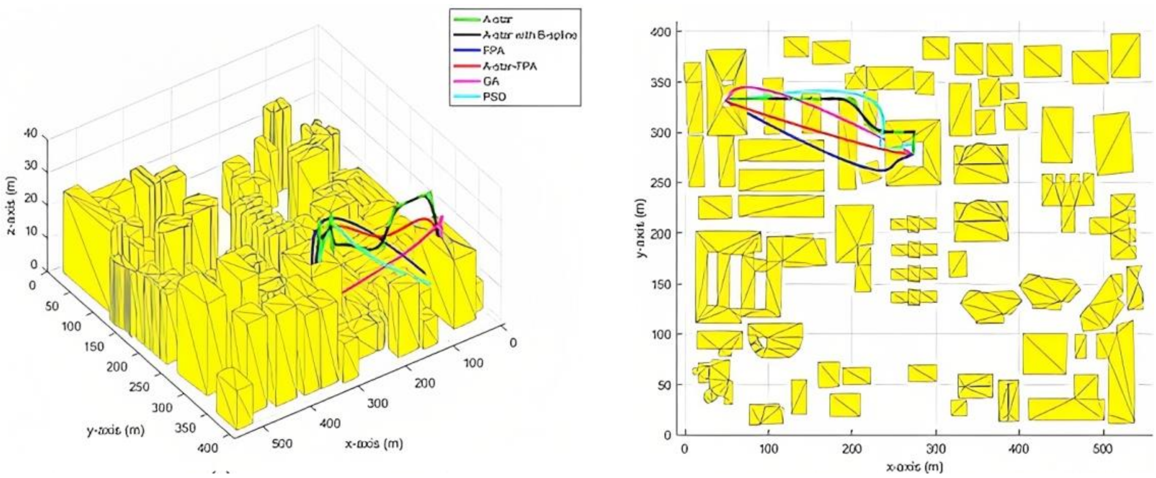


Figure 8. The algorithm's performance in the second scenario

While in the third scenario, only the A* algorithm and the proposed A*-FPA algorithm can find a collision-avoidance 3D path plan with path lengths equal to 285.341 m and 251.536 m, respectively, as shown in Figures 9(a), (b), and 10. Where the A* algorithm is found, the path passes through 14 nodes. While the other algorithm fails after 50 iterations to find a safe path, it requires more iterations to find the optimal path, increasing the computational process.



(a) (b)

Figure 9. The found path in the third scenario is in; (a) the top view and (b) the 3D view

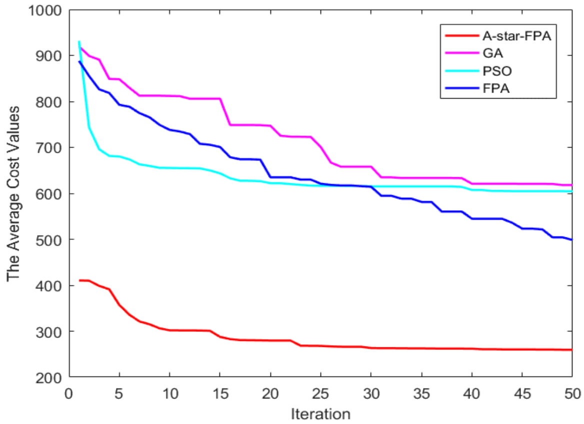


Figure 10. The algorithm's performance in the third scenario

The results demonstrate that the recommended hybrid A*-FPA algorithm improved the UAV's route planning efficiency. The percentages of path best value, mean value, standard deviation value, and worst value enhancement obtained in Table 4 demonstrate that the suggested hybrid algorithm outperforms all other compared algorithms. We also notice that the improved values rise in more complicated situations.

Table 4. The percentage enhanced of A*-FPA at the optimal route and mean path in different scenarios

Scenario no.	Items	A* (%)	FPA (%)	GA (%)	PSO (%)
1	Best	8.65	1.546	3.04	0.566
	Mean	-	2.73	10.755	3.33
2	Best	13.5	1.9	2.2	1.4
	Mean	-	3.23	5.04	4.7
3	Best	13.4	74.3	70.4	79.3
	Mean	-	109.1	138.7	147.8

5. CONCLUSION

This work introduced a hybrid global path-planning algorithm called A*-FPA that balanced the process between the A* exploration ability and the FPA exploitation ability to solve the issue of UAV route planning and obstacle avoidance. According to four criteria-the "best path," "mean path," "standard deviation," and "worst path length"-the suggested algorithm's performance is compared to that of the A*, FPA, GA, and PSO algorithms. The simulation results of the proposed algorithm improved the values of the optimum route length, mean path, standard deviation, and worst path length in all scenarios. The best route length enhancement ratio increased from 0.56% in the first tested scenario to 79.3% in the final one, and the mean route length enhancement ratio increased from 2.73% in the first scenario to 147.8% in the final one. On the other hand, the standard deviation and worst path length results showed that the suggested approach obtained better results than the alternative algorithms. We conclude that the hybrid A*-FPA can be where the suggested algorithm effectively balances the exploitation and exploration processes and keeps the method's performance from slipping below the local optimum. The low standard deviation values across all situations studied ensured that the safest route would be discovered throughout each trial. The hybrid A*-FPA route planning version may be used in dynamic environments.

APPENDIX

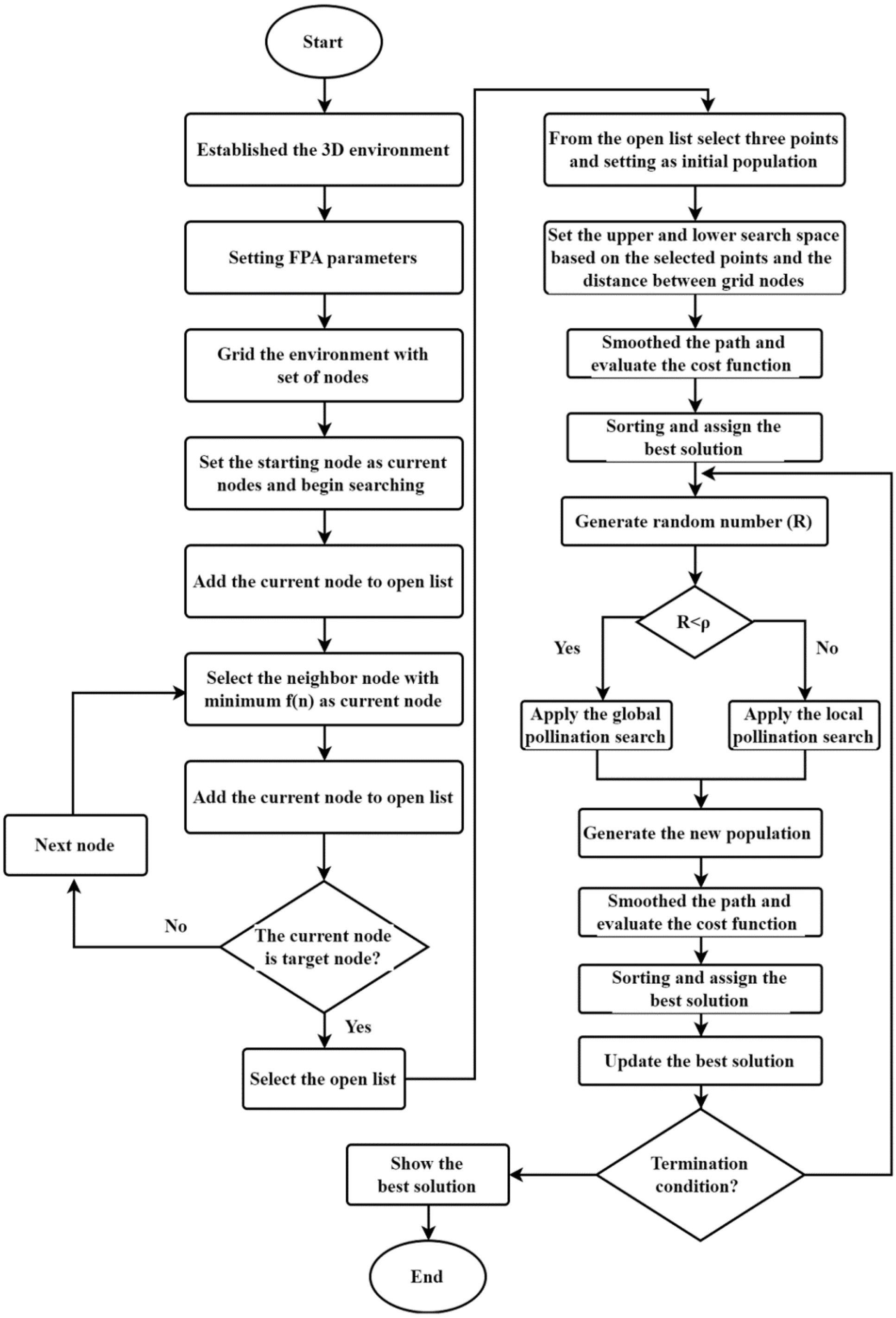


Figure 3. The A*-FPA flow chart process

REFERENCES

[1] N. A. K. Zghair and A. S. Al-Araji, “Intelligent Hybrid Path Planning Algorithms for Autonomous Mobile Robots,” *International Journal of Intelligent Engineering and Systems*, vol. 15, no. 5, pp. 309–325, Oct. 2022, doi: 10.22266/ijies2022.1031.28.

[2] C. Qu, W. Gai, J. Zhang, and M. Zhong, “A novel hybrid grey wolf optimizer algorithm for unmanned aerial vehicle (UAV) path planning,” *Knowledge-Based Systems*, vol. 194, p. 105530, Apr. 2020, doi: 10.1016/j.knosys.2020.105530.

[3] L. D. Jalal, “Three-Dimensional Off-Line Path Planning for Unmanned Aerial Vehicle Using Modified Particle Swarm Optimization,” *International Journal of Aerospace and Mechanical Engineering*, vol. 9, no. 8, pp. 1487–1491, 2015.

[4] B. Abhishek, S. Ranjit, T. Shankar, G. Eappen, P. Sivasankar, and A. Rajesh, “Hybrid PSO-HSA and PSO-GA algorithm for 3D path planning in autonomous UAVs,” *SN Applied Sciences*, vol. 2, no. 11, p. 1805, Nov. 2020, doi: 10.1007/s42452-020-03498-0.

[5] L. Yang, J. Qi, D. Song, J. Xiao, J. Han, and Y. Xia, “Survey of Robot 3D Path Planning Algorithms,” *Journal of Control Science and Engineering*, vol. 2016, pp. 1–22, 2016, doi: 10.1155/2016/7426913.

[6] M. Y. Taha, M. J. Mohamed, and O. N. Ucan, “Optimal 3D Path Planning for the Delivery Quadcopters Operating in a City Airspace,” in *4th International Symposium on Multidisciplinary Studies and Innovative Technologies, ISMSIT 2020 - Proceedings*, IEEE, Oct. 2020, pp. 1–10, doi: 10.1109/ISMSIT50672.2020.9254715.

[7] D. Mandloi, R. Arya, and A. K. Verma, “Unmanned aerial vehicle path planning based on A* algorithm and its variants in 3d environment,” *International Journal of System Assurance Engineering and Management*, vol. 12, no. 5, pp. 990–1000, Oct. 2021, doi: 10.1007/s13198-021-01186-9.

[8] C. Saranya, M. Unnikrishnan, S. A. Ali, D. S. Sheela, and V. R. Lalithambika, “Terrain based D∗ algorithm for path planning,” *International Federation of Automatic Control-PapersOnLine*, vol. 49, no. 1, pp. 178–182, 2016, doi: 10.1016/j.ifacol.2016.03.049.

[9] A. Abbadi, R. Matousek, S. Jancik, and J. Roupec, “Rapidly-exploring random trees: 3D planning,” *Mendel*, no. June, pp. 594–599, 2012, doi: 10.13140/2.1.3632.3848.

[10] A. Israr, Z. A. Ali, E. H. Alkhammash, and J. J. Jussila, “Optimization Methods Applied to Motion Planning of Unmanned Aerial Vehicles: A Review,” *Drones*, vol. 6, no. 5, p. 126, May 2022, doi: 10.3390/drones6050126.

[11] M. Abed, O. Lutfy, and Q. Al-Doori, “A Review on Path Planning Algorithms for Mobile Robots,” *Engineering and Technology Journal*, vol. 39, no. 5A, pp. 804–820, May 2021, doi: 10.30684/etj.v39i5a.1941.

[12] B. K. Oleiwi, A. Mahfuz, and H. Roth, “Application of Fuzzy Logic for Collision Avoidance of Mobile Robots in Dynamic-Indoor Environments,” in *International Conference on Robotics, Electrical and Signal Processing Techniques*, IEEE, Jan. 2021, pp. 131–136, doi: 10.1109/ICREST51555.2021.9331072.

[13] R. Kamil, M. Mohamed, and B. Oleiwi, “Path Planning of Mobile Robot Using Improved Artificial Bee Colony Algorithm,” *Engineering and Technology Journal*, vol. 38, no. 9, pp. 1384–1395, Sep. 2020, doi: 10.30684/etj.v38i9a.1100.

[14] A. Sonmez, E. Kocyigit, and E. Kugu, “Optimal path planning for UAVs using Genetic Algorithm,” in *2015 International Conference on Unmanned Aircraft Systems, ICUAS 2015*, IEEE, Jun. 2015, pp. 50–55, doi: 10.1109/ICUAS.2015.7152274.

[15] R. L. Galvez, E. P. Dadios, and A. A. Bandala, “Path planning for quadrotor UAV using genetic algorithm,” in *2014 International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management, HNICEM 2014 - 7th HNICEM 2014 Joint with 6th International Symposium on Computational Intelligence and Intelligent In*, IEEE, Nov. 2014, pp. 1–6, doi: 10.1109/HNICEM.2014.7016260.

[16] Y. Zhang, J. Guo, R. Zhu, Z. Zhao, and L. Wang, “Path planning based on improved ant colony algorithm,” in *Proceedings - 2020 International Conference on Virtual Reality and Intelligent Systems, ICVRIS 2020*, IEEE, Jul. 2020, pp. 946–949, doi: 10.1109/ICVRIS51417.2020.00230.

[17] A. Mirshamsi, S. Godio, A. Nobakhti, S. Primatesta, F. Dovis, and G. Guglieri, “A 3D Path Planning Algorithm Based on PSO for Autonomous UAVs Navigation,” in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2020, pp. 268–280, doi: 10.1007/978-3-030-63710-1_21.

[18] A. M. and S. Deb, “Mobile Robot Path Planning Using a Flower Pollination Algorithm-Based Approach,” in *Nature-Inspired Computation in Navigation and Routing Problems*, Singapore: Springer Nature, 2019, pp. 127–147, doi: 10.1007/978-981-15-1842-3.

[19] T. Abaas and A. Shabeeb, “Obstacle Avoidance and Path Planning of a Wheeled Mobile Robot Using Hybrid Algorithm,” *Engineering and Technology Journal*, vol. 40, no. 12, pp. 1–12, Dec. 2022, doi: 10.30684/etj.2022.132929.1154.

[20] M. Abdulakareem and F. Raheem, “Development of Path Planning Algorithm Using Probabilistic Roadmap Based on Ant Colony Optimization,” *Engineering and Technology Journal*, vol. 38, no. 3A, pp. 343–351, Mar. 2020, doi: 10.30684/etj.v38i3a.389.

[21] A. A. Kareem, B. K. Oleiwi, and M. J. Mohamed, “Planning the Optimal 3D Quadcopter Trajectory Using a Delivery System-Based Hybrid Algorithm,” *International Journal of Intelligent Engineering and Systems*, vol. 16, no. 2, pp. 427–439, Feb. 2023, doi: 10.22266/ijies2023.0430.34.

[22] B. C. Zhang, C. Wu, Z. X. Pang, Y. Li, and R. K. Wang, “Hybrid Global Optimum Beetle Antennae Search - Genetic Algorithm Based Welding Robot Path Planning,” in *9th IEEE International Conference on Cyber Technology in Automation, Control and Intelligent Systems, CYBER 2019*, IEEE, Jul. 2019, pp. 1520–1524, doi: 10.1109/CYBER46603.2019.9066742.

[23] R. Athira Krishnan, V. R. Jisha, and K. Gokulnath, “Path planning of an autonomous quadcopter based delivery system,” in *2018 International Conference on Emerging Trends and Innovations In Engineering And Technological Research, ICETIETR 2018*, IEEE, Jul. 2018, pp. 1–5, doi: 10.1109/ICETIETR.2018.8529067.

[24] X. Lan, X. Lv, W. Liu, Y. He, and X. Zhang, “Research on Robot Global Path Planning Based on Improved A-star Ant Colony Algorithm,” in *IAEAC 2021 - IEEE 5th Advanced Information Technology, Electronic and Automation Control Conference*, IEEE, Mar. 2021, pp. 613–617, doi: 10.1109/IAEAC50856.2021.9391099.

[25] Y. Li, D. Dong, and X. Guo, “Mobile robot path planning based on improved genetic algorithm with A-star heuristic method,” in *2020 IEEE 9th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)*, IEEE, Dec. 2020, pp. 1306–1311, doi: 10.1109/ITAIC49862.2020.9338968.

[26] A. Shareef and S. Al-Darraji, “Grasshopper optimization algorithm based path planning for autonomous mobile robot,” *Bulletin of Electrical Engineering and Informatics*, vol. 11, no. 6, pp. 3551–3561, Dec. 2022, doi: 10.11591/eei.v11i6.4098.

[27] A. A. Alabdalbari and I. A. Abed, “New robot path planning optimization using hybrid GWO-PSO algorithm,” *Bulletin of Electrical Engineering and Informatics*, vol. 11, no. 3, pp. 1289–1296, Jun. 2022, doi: 10.11591/eei.v11i3.3677.

[28] J. Zhao, X. Zhu, and T. Song, “Serial Manipulator Time-Jerk Optimal Trajectory Planning Based on Hybrid IWOA-PSO Algorithm,” *IEEE Access*, vol. 10, pp. 6592–6604, 2022, doi: 10.1109/ACCESS.2022.3141448.

[29] B. K. Oleiwi, H. Roth, and B. I. Kazem, “Multi Objective Optimization of Path and Trajectory Planning for Non-holonomic Mobile Robot Using Enhanced Genetic Algorithm,” in *Communications in Computer and Information Science*, 2014, pp. 50–62,

doi: 10.1007/978-3-319-08201-1_6.
[30] X. S. Yang, "Flower pollination algorithm for global optimization," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 7445 LNCS, pp. 240–249, Aug. 2012, doi: 10.1007/978-3-642-32894-7_27.
[31] M. Abdel-Basset and L. A. Shawky, "Flower pollination algorithm: a comprehensive review," *Artificial Intelligence Review*, vol. 52, no. 4, pp. 2533–2557, Dec. 2019, doi: 10.1007/s10462-018-9624-4.
[32] L. Biagiotti and C. Melchiorri, *Trajectory planning for automatic machines and robots*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2009, doi: 10.1007/978-3-540-85629-0.

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