Three Dimensional Route Planning for Multiple Unmanned Aerial Vehicles using Salp Swarm Algorithm

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Abstract: Route planning for multiple Unmanned Aerial Vehicles (UAVs) is a series of translation and rotational steps from a given start location to the destination goal location. The goal of the route planning problem is to determine the most optimal route avoiding any collisions with the obstacles present in the environment. Route planning is an NP-hard optimization problem. In this paper, a newly proposed Salp Swarm Algorithm (SSA) is used, and its performance is compared with deterministic and other Nature-Inspired Algorithms (NIAs). The results illustrate that SSA outperforms all the other meta-heuristic algorithms in route planning for multiple UAVs in a 3D environment. The proposed approach improves the average cost and overall time by 1.25% and 6.035% respectively when compared to recently reported data. Route planning is involved in many real-life applications like robot navigation, self-driving car, autonomous UAV for search and rescue operations in dangerous ground-zero situations, civilian surveillance, military combat and even commercial services like package delivery by drones.

Keywords: Deterministic, Meta-heuristic, Nature Inspired Algorithm, Route planning, Salp Swarm Algorithm, UAV

1 Introduction

UAVs have the capability of autonomous navigation which allows them to move towards the goal location in the most optimal fashion, and simultaneously ensure that they do not suffer any collisions with other UAVs or the obstacles present in the environment. The most compelling ability of the UAVs is to operate in complex environments where human operations tend to be very difficult. The time needed to solve the route planning problem is exponential and substantially grows with the increasing complexity of environment since it is an NP-hard problem.

There are two different methods for route planning [1]: offline (or global) route planning – in which the UAV estimates the complete route even before starting any movement; and online (or local) route planning – in which the vehicle simultaneously updates the route and moves towards the destination.

Route planning can be applied to land, air or water – while the vehicle in land corresponds to a 2D environment; in the latter two, the UAV can move in all the three dimensions and corresponds to a 3D environment. This paper considers the problem of global route planning for multiple UAVs in 3D environment.

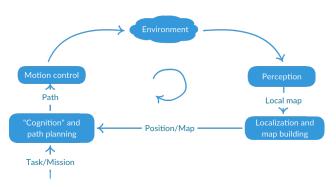


Fig. 1: Robot Navigation Structure [23]

As shown in Figure 1, the underlying architecture of route planning can be divided into four components:

- 1.Perception: Vehicle utilizes the sensors to devise meaningful information of the surroundings. If the agent/robot possesses full knowledge of the environment at all time then the route planning is global otherwise it is local.
- 2. **Localization**: Vehicle identifies its location in the operating environment
- 3.Cognition and path planning: Vehicles decide in which direction it should steer to reach to the goal location in accordance with the deterministic or meta-heuristic algorithm used.
- 4.Motion control: Vehicle regulates its motion in order to achieve the desired trajectory.

Meta-heuristic algorithms can be termed as stochastic algorithms with randomization and local search [1]. The main reason to choose a meta-heuristic based SSA algorithm for route planning is that these algorithms generate near-optimal routes in significantly less time in complex environments which can not be achieved by deterministic algorithms. Meta-heuristic algorithms are very efficient and have a wide range of applications since they can achieve practical solutions for various problems.

Meta-heuristic algorithms are classified as *Evolutionary* and *Swarm Intelligence*. The former algorithm tries to mimic the approach of evolution in nature; and the latter tries to mimic the intelligence of herds, swarms, flocks in nature. The primary source of inspiration for these techniques emerge from the collective behavior of creatures. Some of the evolutionary algorithms include Genetic Algorithm, Differential evolution, Biogeography-Based Optimization (BBO), Evolution strategy; while swarm intelligence includes Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Dragonfly Algorithm (DA), Cuckoo Search (CS), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), Salp Swarm Algorithm (SSA) among others.

2 Related Work

The problem of route planning by autonomous UAVs in a 2D environment has been solved by many approaches like cell decomposition method [2], Voronoi diagram, visibility graph [3], potential field approach, and rapidly exploring random trees (RRTs) [4], deterministic search algorithm Dijkstra [5] and heuristic based algorithms (A* and D*) [6]. The algorithms mentioned above are proactive, so

they are not effective solutions for route planning and suffer from local minima stagnation and considerable time complexity.

In a 3D environment various meta-heuristics algorithms like Genetic Algorithm (GA) [7], Predator-Prey Pigeon Inspired Optimization (PPPIO) [8], Whale Optimization Algorithm (WOA) [9], Biogeography-Based Optimization (BBO) [10], Particle Swarm Optimization (PSO) [11], Invasive Weed Optimization (IWO) [12], Glowworm Swarm Optimization (GSO) [13] etc. have been applied. Md. Arafat [14] presented Bacterial Foraging Optimization (BFO) to compute the shortest path in a dynamic unknown environment and used Gaussian cost function. Similarly, Edin Dolicanin [15], applied a modification of BrainStorm Optimization (BSO) Algorithm for finding the optimal path of an unmanned combat aerial vehicle (UCAV) while considering fuel consumption and safety degree as a metric. Zhang et al. [16] applied Grey Wolf Optimizer (GWO) to path planning issue on the battlefield. Phung et al. [17] improved discrete PSO technique. He devised it to path planning for surface inspection using UAV vision. Yaoming Zhou [18] proposed a bioinspired computing algorithm that is inspired from plant growth mechanism and applied it to the problem of path planning.

In general, nature-inspired algorithms have displayed excellent performance in solving intricate real-world problems like route planning. In this paper, the extension of some above-listed algorithms for finding routes for multiple UAVs in a 3D environment is presented. This paper proposes the use of Salp Swarm Algorithm(SSA) which is a meta-heuristic optimization algorithm and proposed by Mirjalili et al. [19] to solve the route planning problem. SSA is influenced by swarming behavior of salps while foraging and navigating in oceans. In [19], it was shown that SSA significantly outperforms other popular meta-heuristic algorithms. By using several stochastic operators, the problem of local optima stagnation is avoided in multi-modal search landscapes. The algorithm is applicable for single as well as multi-objective optimization tasks.

The further structure of the paper is formulated into following sections. Section 3 illustrates the methodology of multiple autonomous UAV route planning and a description of the environment. Section 4 gives a thorough explanation of the SSA. Section 5 illustrates the implementation and final results obtained by comparing SSA with other meta-heuristic algorithms. Section 6 finally concludes the paper.

3 Methodology

The proposed methodology can be organized into the following segments. First, a description of problem statement is given and after that terrain construction is described. Following that, the cost function for the optimization is presented, and then finally the trajectory for autonomous UAVs is generated.

3.1 Problem Statement

The problem of route planning of multiple UAVs in 3D environment can be viewed as a mapping to a function in which start and goal location are presented as inputs and obtain an optimal trajectory in terms of output. The primary interest of route planning is to generate an optimal, collision-free route with the least cost.

$$f(start_i, goal_i) \rightarrow trajectory_i$$
 (1)

where $start_i$ represents start location of the i^{th} UAV $(X_{start}, Y_{start}, Z_{start})$; $goal_i$ represents the goal location of the i^{th} UAV $(X_{goal}, Y_{goal}, Z_{goal})$; $trajectory_i$ represents a collision-free trajectory of i^{th} UAV [24].

The initial position of n UAVs can be represented with the help of the following matrix:

Where pos_i^m represents position i^{th} UAV in m dimensional space. Since a 3D space is used, therefore M=3. The aim is to decrease path length (pi_i) for each given UAV by following objective function:

$$(\pi_1^*, \pi_2^*, \dots, \pi_n^*) = \arg\min_{\pi_1, \pi_2, \dots, \pi_n} \sum_{j=1}^n c_j \pi_j$$
 (3)

subject to constraint

$$\chi_{ij}(\pi_i, \pi_j) = 0 \quad \forall i, j = 1, 2, ..., n$$
(4)

Where i and j represent the different UAVs; π_i denotes the path of i^{th} UAV which is computed by

$$\pi_i = \sqrt{(x_i - x_t)^2 + (y_i - y_t)^2 + (z_i - z_t)^2}$$
 (5)

Where, c_i denotes cost associated with path π_i [24].

 χ_{ij} represents violation of the same path constraints between the trajectories of UAV i and j. So i and j are taken from non-intersection paths from source to destination. Figure 2 shows the paths followed by the UAVs to reach their destinations while not suffering any collisions in between.

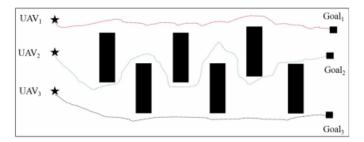


Fig. 2: Trajectory generated by the multiple UAVs in a 2D environment [20]

3.2 Terrain construction

To understand and solve the problem of route planning, an environment is required to simulate the UAVs to generate a route. The environment will contain several areas where the movement is prohibited, and those areas can be termed as obstacles. To prevent a collision, UAVs shall stay away from these areas. Obstacles of cuboidal shape with distinct sizes are chosen however in the real-life situations, obstacles generally don't possess a specific geometrical shape. To perform modeling in an environment where obstacles do not have a perfect geometrical shape is challenging and hampers the experimentation. Irregular obstacles are also included in modeling and testing of environment, and SSA will avert the uneven obstacles efficiently.

Two dimensional route planning is related to the planning of motion for vehicles on land and also in air or underwater while restricting one dimension. Simulation in 3-D environment is complex and requires expensive computations to generate the routes. At the same time, a 3D environment better models the complex real-life scenarios.

The details of the boundary, starting positions of UAVs and goal locations, as well as positions of obstacles for four maps used are depicted in Tables 1, 2 and 3 respectively[13]. Using a different set of maps, as presented in Figure 3, performance of SSA is compared and analyzed with deterministic and other meta-heuristic algorithms.

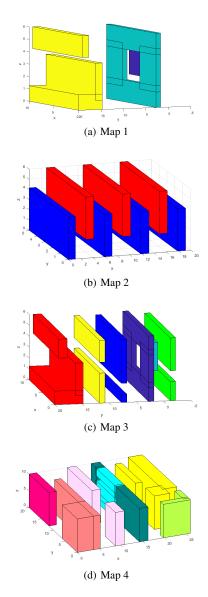


Fig. 3: Depiction of maps of 3D environment

Table 1 3D Map Boundary Representation

Map	Start Boundary	End Boundary
Map 2 Map 3	(0, -5, 0) (0, 0, 0) (0, -5, 0) (0, 0, 0)	(10, 20, 6) (20, 5, 6) (10, 20, 6) (26, 20, 10)

3.3 Cost Function

Due to the random nature of generated routes, there exists a possibility that the UAVs might collide with the obstacles and cannot continue its motion, so the goal location cannot be reached. So, various costs are required to be introduced in the route planning problem like fuel cost, cost due to sharp turns and cost due to an incomplete route. The various costs involved can be illustrated as[13]:

• C_{fuel} : The cost of fuel which depends on length of the route followed. This cost is less when the route followed has a smaller length, which in turn leads to less consumption of fuel and lower time to reach the goal.

- C_{divergence}: This cost is governed by frequency of sharp turns present in route. Lower the sharp turns the smoother and stable the route is.
- • C_{gap} : This cost corresponds to the separation among the goal and the route's end when the UAVs fail to reach the goal location. This situation could arise due to a significant obstacle which lies in between the route to goal. This cost corresponds to the highest interest amongst all the costs and assigned with the highest priority. This cost should have a zero value in the optimal solution.

The generated route $R_{(x,y,z)}$ to the goal location can be presented as a sequence of points from the source location as follows:

$$R_{x,y,z} = \{S, a_1, a_2, a_3, a_4, \dots a_n, G\}$$
 (6)

where, S represents the start location; G represents the goal location; $a_1, a_2, ... a_n$ represent the points occurring in the route.

To determine the cost of the fuel, the speed of the UAV is assumed to be constant during route planning. Thus, the cost of the fuel can be obtained by using total distance traveled by the UAVs. The cost of fuel is presented using Equation 7.

$$C_{fuel} = \sum (D_{x,y,z}) \tag{7}$$

The cost due to sharp turns occurs when change in direction from a_{j-1} to a_j do not match the change in direction from a_j to a_{j+1} . It can be computed by searching the cases in obtained route with a considerable amount of turn in the angle between the two. This cost will increase with the increase of sharp turns in the planned route. This cost can be inferred from equation 8.

$$C_{divergence} = \text{number of turning points in route}$$
 (8)

Now the most significant cost, i.e., C_{gap} is computed using the Euclidean distance. The two required points are end point of route and the goal location. If the endpoint and goal location is the same than this cost is set to 0 else, it is determined with the help of equation 9.

$$c_{gap} = \sqrt{(X_{end} - T_x)^2 + (Y_{end} - T_y)^2 + (Z_{end} - T_z)^2}$$
 (9)

 $(X_{end},Y_{end},Z_{end})$ represent the endpoints of the generated route; (T_x,T_y,T_z) represents the target location.

The total cost of a route can be computed using equation 10.

$$C_{total} = P_1 \times C_{fuel} + P_2 \times C_{divergence} + P_3 \times C_{gap} \quad (10)$$

The total cost function helps to achieve the optimal route from the route set.

Here P_1 , P_2 , P_3 are the experimental parameters and their values are actuated with the help of experiments and constraints of the problem description. In scenarios where a more substantial route length is taken as a preference, then P_1 is assigned a higher value. Similarly P_2 assigns inclination towards the route smoothness. From P_3 , it is ensured that the route planned reaches the goal. The UAVs posses a propensity to include information regarding their locality only, and for the subsequent increment, they might alter their location among one of the cells in the neighborhood. Thus, UAVs do not have any prior knowledge regarding at what time and location it will face an obstacle; that is why UAVs steadily continue to modify their paths whenever they encounter the obstacles.

3.4 Trajectory generation for multiple UAVs

The generated trajectory by the SSA may include some sharp turns which practically are not feasible for UAVs to follow. So, it becomes crucial to smoothen the generated route. The movement and speed of the UAVs can be presented using polynomial functions for vehicular mobility. The polynomial function involves the component of

Table 2 3D Map Start and Goal Representation

Мар	Start Position	Goal Position
Map 1	(2, 10, 2) (1, -4, 1) (9.2, 17, 3) (9.2, 10, 3) (0.1, 10, 2)	(1, -4, 1) (0.1, 17, 3) (9, -4, 1) (0.9, -4, 5) (9, 10, 2)
Map 2	(0, 1, 5) (0, 2, 5) (0, 3, 5) (19, 4, 5) (19, 5, 5)	(19, 0, 5) (19, 5, 5) (19, 4, 5) (0, 3, 5) (0, 1, 5)
Map 3	(2, 10, 2) (1, -4, 1) (9.2, 17, 3) (9.2, 10, 3) (0.1, 10, 2)	(1, -4, 1) (0.1, 17, 3) (9, -4, 1) (0.9, -4, 5) (9, 10, 2)
Map 4	(17, 2, 5) (3, 2, 5) (7, 2, 5) (7, 18, 7) (17, 18, 5)	(21.5, 12, 4) (6, 6, 5) (13, 1, 3) (12, 14, 6) (22, 14, 8)

Table 3 3D Map Obstacle representation

Obs	Map 1	Map 2	Мар 3	Map 4
1	(0, 2, 4.5) - (10, 2.5, 6)	(3.1, 0, 2.1) - (3.9, 5, 6)	(0, -2, 0) - (10, -1.5, 1.5)	(0, 12, 0) - (1.5, 20, 10)
2	(0, 2, 1.5) - $(3, 2.5, 4.5)$	(9.1, 0, 2.1) - (9.9, 5, 6)	(0,-2,3) - $(10,-1.5,5.5)$	(0, 0, 0) - $(5, 6, 10)$
3	(7, 2, 1.5) - (10, 2.5, 4.5)	(15.1, 0, 2.1) - (15.9, 5, 6)	(0, 2, 0) - $(10, 2.5, 1.5)$	(4, 0, 0) - (5, 16, 10)
4	(0, 2, 0) - $(10, 2.5, 1.5)$	(0.1, 0, 0) - (0.9, 5, 3.9)	(0, 2, 4.5) - $(10, 2.5, 6)$	(9, 10, 0) - (10.5, 20, 10)
5	(0, 15, 0) - $(10, 20, 1)$	(6.1, 0, 0) - (6.9, 5, 3.9)	(0, 2, 1.5) - $(3, 2.5, 4.5)$	(9, 0, 0) - $(10.5, 4, 10)$
6	(0, 15, 1) - (10, 16, 3.5)	(12.1, 0, 0) - $(12.9, 5, 3.9)$	(7, 2, 1.5) - $(10, 2.5, 4.5)$	(14.5, 0, 0) - (16, 10, 10)
7	(0, 18, 4.5) - (10, 19, 6)	(18.1, 0, 0) - (18.9, 5, 3.9)	(3, 0, 2.4) - (7, 0.5, 4.5)	(14.5, 10, 8) - (16, 18, 10)
8	(3, 0, 2.4) - (7, 0.5, 4.5)	-	(0, 15, 0) - $(10, 20, 1)$	(14.5, 10, 3.5) - (16, 18, 6)
9	-	-	(0, 15, 1) - $(10, 16, 3.5)$	(14.5, 10, 0) - (16, 18, 1.5)
10	-	-	(0, 18, 4.5) - (10, 19, 6)	(14.5, 18, 0) - (16, 20, 10)
11	-	-	(0, 7, 0) - $(10, 7.5, 0.5)$	(19, 10, 0) - (20, 18, 10)
12	-	-	(0, 7, 2) - $(10, 7.5, 5.5)$	(20, 4, 0) - (23, 7, 10)
13	-	-	(0, 11, 0) - (10, 11.5, 2.5)	(20, 0, 0) - (26, 1, 10)
14	-	-	(0, 11, 4) - (10, 11.5, 5.5)	(23, 6, 0) - (26, 20, 10)
15	-	-	-	(25, 1, 0) - (26, 4, 10)

time. A continuous route is generated by the fifth-degree polynomial, which indicates that the first derivatives are consistent. The polynomial derivative can be determined efficiently to obtain the results of the campaign in this manner. A conventional fifth order time polynomial function[24] is represented using equation 11.

$$S(t) = a_5 t^5 + a_4 t^4 + a_3 t^3 + a_2 t^2 + a_1 t^1 + a_0$$
 (11)

While generating the trajectory, the sub-points are obtained in the initial phase. Sub-point can be considered as a necessary point in the confined route, which assists the UAV to avert any obstacle or steep turn. To produce a smooth route, the speed and movement of UAV traveling through sub-points are utilized by the fifth order polynomial based trajectory fitting strategy[24].

The main objective of using SSA for multiple UAV route planning in a 3D environment is:

- •to localize the UAVs and destination location.
- to plan a route between multiple UAVs and their corresponding targets and simultaneously ensure that no UAV collides with each other or any obstacle.

4 Salp Swarm Algorithm

Salp is a sea creature having a transparent barrel-shaped body. It is a part of the Salpidae family. It's movement is governed by pumping of water through the body and as propulsion to move forward. SSA is inspired by the swarming behavior of salps while foraging and navigating in the water. The shape of a salp is shown in Figure 4(a). The swarm formed by the salps in deep oceans is referred to as a salp chain. This chain is illustrated in Figure 4(b). This algorithm was first developed by Mirjalili et. al. in 2017[19]. The primary reason to choose SSA for route planning was its simplicity and since the inspiration for the algorithm is from the natural navigating and foraging behavior of the salps in the ocean in search of food. With respect to multi-UAV route planning, the foraging phase of the salp chains can be considered as a search for different targets in the environment and the navigating phase can be regarded as connecting the points in the environment to obtain waypoints for the generated path length.

For understanding the salp chains, a mathematical model was developed. The population is broken down into 2 segments- leader

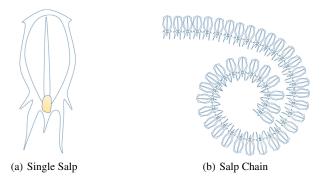


Fig. 4: Schematic Diagram of Salps [19]

and followers. Leader salp is present at the front of the chain while remaining salps are recognized as followers. The salp at the front escorts the swarm while the remaining salps follow each other and leader (either directly or indirectly).

Similarly to other swarm-based techniques, the position of salps is defined in an n-dimensional search space where n denotes number of variables for a given problem. Thus, the position of all salps is saved in a two-dimensional matrix called x. It is an assumption that there exists a food source called F in the search space as the swarms' target.

The complete working of SSA can be observed from the following equations.

Equation 12 updates the position of the leader:

$$x_j^1 = \begin{cases} F_j + c_1((ub_j - lb_j)c_2 + lb_j) & c_3 \ge 0 \\ F_j - c_1((ub_j - lb_j)c_2 + lb_j) & c_3 < 0 \end{cases}$$
 (12)

Where x_j^1 = position of the leader; F_j = position of the food source; ub_j and lb_j are upper and lower bounds in j^{th} dimension; c_1, c_2, c_3 are uniform random numbers.

In Equation 13, c_1 maintains a balance between exploration & exploitation phase:

$$c_1 = 2e^{-\left(\frac{4l}{L}\right)^2} \tag{13}$$

Where, l: current iteration, L: maximum number of iterations.

Exploration is defined as the phase in which the algorithm tries to explore the search space. The avoidance of local solutions takes place in this phase. After the exploration comes the exploitation phase in which the primary concern is to improvise the solutions explored in the exploration phase.

Equation 14 updates position of salps except for the leader:

$$x_j^i = \frac{1}{2}(x_j^i + x_j^{i-1}) \tag{14}$$

The pseudocode of SSA algorithms is given in Algorithm 1.

Algorithm 1 SSA Algorithm

```
1: Initialize the salp population x_i (i = 1, 2, ..., n) considering ub
   while (end condition is not satisfied)
3:
   Calculate the fitness of each search agent (salp)
   F = the best search agent
5: Update c_1 by Eq. (2)
        for each salp (x_i)
 7:
            if (i == 1)
8:
                 Update the position of the leading salp by Eq. (1)
9.
10:
                 Update the position of the follower salp by Eq. (4)
11:
            end
12:
        end
         Amend the salps based on the upper and lower bounds of
13:
    variables
14: end
15: return F
```

Some assumptions are made in the research to get more efficient and useful results. The assumptions made here are as follows:

- •The UAV is considered as a point object.
- •The speed of the UAV is kept constant during the entire simulation.
- •Upon reaching the target point, a UAV can stop immediately irrespective of the momentum.

SSA algorithm has computational complexity $O(t(d \times n + Cof \times n))$

where t= number of iterations; d= number of variables (dimension); n= number of solutions; and Cof= the cost of the objective function.

5 Implementation Procedure

To validate the effectiveness of SSA on multiple UAV route planning problem in a static 3D environment, a set of experiments have been performed in MATLAB. Matlab 2017a version and a PC with intel i7 processor, 3.40 GHz of CPU and 8 GB of RAM were chosen for performing the experimentation. In this section, experimental simulation is described, which is divided into two experiments. Then convergence analysis of the SSA algorithm on different maps is presented.

5.1 Simulation

Before analyzing the performance of SSA in a 3D environment for multi-UAV route planning, it is first analyzed in a 2D environment and its performance as compared to deterministic and other meta-heuristic algorithms, is examined. To illustrate the above experiments, a different set of maps corresponding to a different environment have been taken.

5.1.1 Experiment 1: The performance of different algorithms is investigated in a 2D environment whose layout is given in Table 4.

Table 4 Static 2D Environment Layout[13]

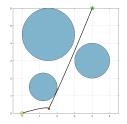
Obs No	Center (unit)	Radius (units)
1	(1.5, 4.5)	1.5
2	(4.0, 3.0)	1.0
3	(1.2, 1.5)	0.8

The initial parameters and constants for the algorithms used in experimentation are listed in Table 5.

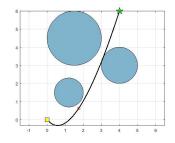
Table 5 Parameter Setting for the SSA[20]

Algorithm	Parameters	Values
SSA	Random Number 1 (c_1) Random Number 2 (c_2) Random Number 3 (c_3)	[0, 1] [0, 1] [0, 1]

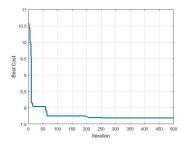
The circular shape in the environment can be modeled as obstacles which should be completely avoided by the vehicle to prevent a collision. The start location of the vehicle was taken as (0,0) and the goal location as (4,6) [13]. The initial experiments of SSA for route planning in 2D environment are performed to test the effectiveness of the algorithm implementation and to have a conjecture on the quality of solution for the 3D path planning of UAV. The convergence curve and planned routes for SSA are illustrated in Figure 5.



(a) Initial path generated during application of SSA for 2D environment.



(b) Final obtained path



(c) Best cost vs number of iteration graph

Fig. 5: Simulation of SSA in 2D environment

The Figure 5 depicts convergence analysis of SSA in the 2D arena simulated above. From Figure 5(c) it is clear that SSA converges quickly and there is little change in the cost with further increase in the number of iterations. The results of different algorithms for with respect to the cost and time in the 2D arena for single bot route planning in static environment are presented in Table 6.

Table 7 Execution time and best cost of algorithms for Map 1 for different population size and max iterations

Algorithm	Pop. Size	Iterations	Best Cost (UAV_1) (cm)	Best Cost (UAV_2) (cm)	Best Cost (UAV_3) (cm)	Best Cost (UAV_4) (cm)	Best Cost (UAV_5) (cm)	Overall Time (sec)
WOA	20	25	215	310	283	232	92	57.64
SCA	20	25	199	306	293	232	92	59.90
GSO	20	25	221	296	283	236	92	57.50
PSO	20	25	221	296	283	232	92	57.15
IBA	20	25	215	308	279	232	92	72.15
BBO	20	25	201	322	299	232	92	65.70
GWO	20	25	201	284	295	232	92	48.50
SSA	20	25	202	284	290	230	92	45.30
WOA	25	40	199	308	285	228	92	65.75
SCA	25	40	213	296	285	232	94	67.35
GSO	25	40	201	284	291	230	96	63.49
PSO	25	40	207	298	285	232	94	91.27
IBA	25	40	208	300	279	230	92	92.32
BBO	25	40	201	300	289	232	92	70.40
GWO	25	40	201	284	295	232	92	56.98
SSA	25	40	200	280	285	230	92	50.03

Table 6 Results in static 2D environment

Algorithm	Population	Iteration	Best Cost (points)	Time (units)
WOA	150	500	8.0131	194.9152
SCA	150	500	8.0042	197.0136
GSO	150	500	8.0236	196.3792
PSO	150	500	8.0234	196.3822
IBA	150	500	7.9321	192.8920
BBO	150	500	7.9803	191.2722
GWO	150	500	7.9560	189.4108
SSA	150	500	7.9340	186.4025

5.1.2 Experiment 2: After analyzing the performance of SSA in a 2D environment, simulations are performed in a 3D environment. A set of four different maps are taken whose layouts are depicted in Table 3.

The start and the end point concerning different obstacle number show the location of two diagonally opposite corners of the cuboid. Every map has different dimensions, different start, goal locations along with different lower and upper bound as given in Tables 1 and 2.

The initial parameters and constants for different algorithms are the same as in the case of a 2D environment and are given in Table 5. Figure 6 shows the trajectory generated by SSA on various maps.

For map 1, 2 and 3 all the algorithms listed above were able to find the paths without any collisions. Map 4 is relatively complex and not all the algorithms discovered collision-free path in first run. SSA performed satisfactorily in map 4 and discovered a collision-free path in all of the multiple runs. To compare performance of different algorithms wrt time and cost, Tables 7 - 10 are formulated.

The results from the tables can be visualized in Figure 7.

5.2 Convergence analysis of SSA algorithm

By analyzing the following Tables 11-14, it becomes evident that the SSA algorithm generates near-optimal results in significantly fewer iterations if there are no obstacles in the workspace. A number of iterations are required to converge towards the optima when obstacles are presented in the workspace; but after completing 15-20 iterations, results do not alter even if more increments are introduced.

As seen in Figure 8, the execution time of algorithms are comparable to recently reported data [16], when a simple environment like Map 1 and 2 is considered. For complex environment like Map 4, the SSA achieves low time complexity and more influencing results. Thus, SSA becomes suitable for real-life scenarios like route planning for multiple UAVs in a complex real-life environment.

The average percentage improvement in cost and time of SSA algorithm with respect to GWO algorithm on Maps 1 to 4 as given in Tables 7 to 10, are calculated by equations 15 and 16.

$$\frac{1}{4} \times \sum_{i=1}^{4} \left(\frac{1}{2} \times \sum_{j=1}^{2} \left(\frac{1}{5} \times \frac{\sum_{k=1}^{5} Cost \ of \ GWO - \sum_{k=1}^{5} Cost \ of \ SSA}{\sum_{k=1}^{5} Cost \ of \ GWO} \times 100 \right) \right)$$
(15)

where i=1 to 4 represents Map 1, 2, 3 or 4, j corresponds to results with respect to two different number of iterations for each map. The innermost summation in equation 15 calculates the effect of costs of all the five UAVs.

For Map 1, the improvement of SSA as compared to GWO is 1.04%. Similarly for Maps 2, 3 and 4, the improvements are 0.81%, 0.94% and 2.21%. Therefore using formula 15 we get the percentage average improvement in cost of SSA as 1.25%.

$$\frac{1}{4} \times \sum_{i=1}^{4} \left(\frac{1}{2} \times \sum_{j=1}^{2} \left(\frac{Time\ of\ GWO-Time\ of\ SSA}{Time\ of\ GWO} \times 100 \right) \right) \quad (16)$$

The percentage improvement in time of SSA is computed to be is 9.40%, 6.90%, 2.27% and 5.57% for Maps 1, 2, 3 and 4 respectively. The percentage average improvement in time of SSA when compared to performance of GWO is 6.035%.

5.3 Comparison with other meta-heuristic algorithms

Since there is no prior information regarding the best meta-heuristic, that is why various meta-heuristic algorithms are utilized for solving multiple UAVs route planning problem. Different algorithms like IBA, BBO, GSO, PSO, WOA, SCA, GWO, and SSA were tried, and it was observed that SSA has the best performance among them. SSA exhibits simplicity since it requires significantly fewer parameters, which are c_1, c_2 and c_3 . This algorithm is also highly flexible since it is applicable to various types of problems and even its architecture need not to be changed. It has a gradient-free mechanism; thus, the need to calculate derivatives of search spaces is avoided. It optimizes the problem in stochastic fashion and prevents local optima stagnation which makes it suitable for solving multi-modal optimization problems.

As stated in No Free Lunch (NFL) [22], there is no particular meta-heuristic which is best for handling all optimization tasks. So a situation can arise, where a particular meta-heuristic might outperform all other algorithms significantly, but the same meta-heuristic can severely give a bad performance for some other set of issues.

 Table 8
 Execution time and best cost of algorithms for Map 2 for different population size and max iterations

Algorithm	Pop. Size	Iterations	Best Cost (UAV_1) (cm)	Best Cost (UAV_2) (cm)	Best Cost (UAV_3) (cm)	Best Cost (UAV_4) (cm)	Best Cost (UAV_5) (cm)	Overall Time (sec)
WOA	20	25	345	333	323	417	341	145.67
SCA	20	25	333	323	343	385	455	142.90
GSO	20	25	355	325	327	387	391	136.27
PSO	20	25	333	313	337	365	423	136.06
IBA	20	25	313	381	365	393	401	138.54
BBO	20	25	375	405	629	758	389	256.87
GWO	20	25	321	381	317	353	375	132.90
SSA	20	25	321	378	313	352	375	125.76
WOA	30	40	313	311	371	367	403	152.20
SCA	30	40	357	341	351	403	373	153.87
GSO	30	40	339	321	317	333	319	146.29
PSO	30	40	325	343	299	327	377	197.94
IBA	30	40	331	343	397	341	355	146.01
BBO	30	40	387	375	345	704	389	266.83
GWO	30	40	319	313	315	333	345	142.90
SSA	30	40	318	305	312	329	342	130.87

 Table 9
 Execution time and best cost of algorithms for Map 3 for different population size and max iterations

Algorithm	Pop. Size	Iterations	Best Cost (UAV_1) (cm)	Best Cost (UAV_2) (cm)	Best Cost (UAV ₃) (cm)	Best Cost (UAV_4) (cm)	Best Cost (UAV_5) (cm)	Overall Time (sec)
WOA	20	25	219	328	343	256	94	95.02
SCA	20	25	235	302	393	278	92	99.75
GSO	20	25	219	322	339	294	92	108.69
PSO	20	25	231	324	371	244	94	95.76
IBA	20	25	203	320	425	268	92	102.47
BBO	20	25	215	346	716	266	94	108.74
GWO	20	25	213	300	355	274	94	92.46
SSA	20	25	210	300	345	274	94	90.30
WOA	25	40	245	308	347	246	96	101.81
SCA	25	40	225	280	369	246	92	105.79
GSO	25	40	215	324	335	254	92	141.91
PSO	25	40	215	318	333	254	92	146.95
IBA	25	40	247	324	375	302	92	151.41
BBO	25	40	215	346	716	266	94	108.74
GWO	25	40	201	312	339	254	92	104.87
SSA	25	40	202	305	340	250	91	102.55

 Table 10
 Execution time and best cost of algorithms for Map 4 for different population size and max iterations

Algorithm	Pop. Size	Iterations	Best Cost (UAV_1) (cm)	Best Cost (UAV_2) (cm)	Best Cost (UAV_3) (cm)	Best Cost (UAV_4) (cm)	Best Cost (UAV_5) (cm)	Overall Time (sec)
WOA	20	25	256	388	459	318	122	229.66
SCA	20	25	259	383	457	320	122	211.86
GSO	20	25	249	352	369	324	122	141.91
PSO	20	25	261	354	401	274	124	95.76
IBA	20	25	233	350	455	298	122	102.47
BBO	20	25	245	376	746	296	124	274.43
GWO	20	25	243	330	385	304	124	92.46
SSA	20	25	242	325	385	281	124	85.20
WOA	25	40	256	365	359	309	122	247.13
SCA	25	40	260	374	358	308	122	211.42
GSO	25	40	245	354	365	284	122	108.69
PSO	25	40	245	348	363	272	122	146.95
IBA	25	40	277	354	405	332	122	151.41
BBO	25	40	231	350	355	302	122	108.74
GWO	25	40	255	342	369	284	122	104.87
SSA	25	40	250	322	370	276	122	101.44

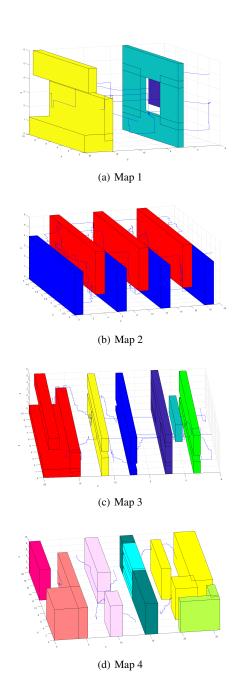


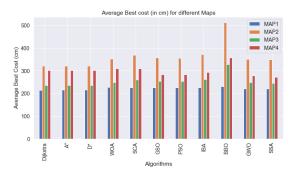
Fig. 6: Simulation of SSA on Maps

Table 11 Average best cost (in cm) per iteration count for Map 1

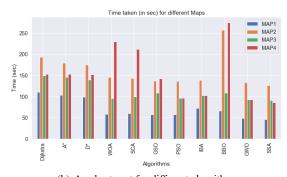
Iteration	GWO	GSO	PSO	BBO	IBA	WOA	SCA	SSA
1	250.80	260.80	252.00	419.79	328.40	256.40	267.20	256.65
5	238.40	245.20	238.80	264.80	249.60	239.20	238.80	235.55
10	228.80	230.00	236.80	243.69	238.40	229.40	236.20	224.80
15	222.80	228.40	228.80	242.40	237.20	224.40	226.80	219.60
20	221.20	227.20	228.60	232.00	234.60	222.40	225.20	218.65
25	220.80	226.80	220.80	226.40	234.00	221.60	222.80	218.05
30	219.60	224.20	224.40	226.00	228.80	219.80	221.60	217.80
35	219.20	222.40	224.00	224.40	226.40	219.20	219.20	217.40

6 Conclusion and future scope

This paper proposes the use of SSA for solving multiple UAV route planning problem in a 3D environment. After investigating the performance of SSA in various experimental scenarios, it is concluded that SSA takes the least time in all the cases when compared with deterministic and other meta-heuristic algorithms and finds an optimal route in both 2D and 3D environment. In some of the cases,



(a) Time taken for different algorithms



(b) Avg best cost for different algorithms

Fig. 7: Time and Cost Graphs for Different Algorithms

Table 12 Average best cost (in cm) per iteration count for Map 2

Iteration	GWO	GSO	PSO	BBO	IBA	WOA	SCA	SSA
1	644.03	644.88	698.75	698.56	1038.79	690.40	696.60	621.92
5	392.80	394.26	425.67	474.20	683.41	396.00	398.20	440.76
10	385.40	391.40	415.60	422.60	512.52	386.60	388.80	382.50
15	361.00	390.40	398.60	385.40	507.04	374.60	373.80	347.81
20	355.00	390.20	394.40	379.80	452.02	360.00	372.60	338.69
25	348.20	359.80	378.60	377.40	432.97	353.80	352.20	330.18
30	346.20	356.20	362.20	375.80	431.46	349.80	351.40	325.74
35	343.00	354.20	354.80	374.20	422.72	347.00	346.20	321.22

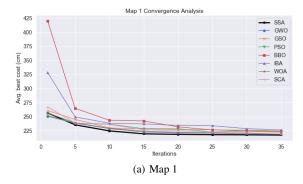
 Table 13
 Average best cost (in cm) per iteration count for Map 3

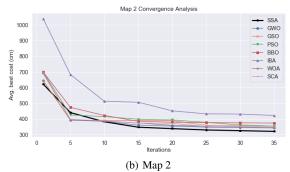
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Iteration	GWO	GSO	PSO	BBO	IBA	WOA	SCA	SSA
1	312.35	315.60	316.40	616.88	745.22	359.20	401.20	409.25
5	272.60	274.00	304.80	356.00	449.28	282.00	314.00	341.50
10	262.80	269.20	265.20	342.45	367.28	265.60	296.80	273.46
15	257.60	264.00	263.60	283.20	358.20	258.20	261.20	244.60
20	251.60	256.40	258.20	276.40	319.23	252.40	254.00	241.86
25	250.80	246.80	250.00	276.00	271.60	252.20	251.60	239.90
30	245.40	246.00	248.80	274.80	268.00	251.20	247.20	239.05
35	245.00	245.80	248.60	272.80	266.40	251.20	247.00	237.65

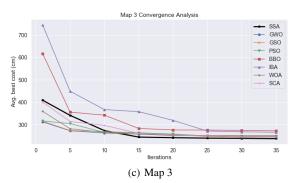
Table 14 Average best cost (in cm) per iteration count for Map 4

Iteration	GWO	GSO	PSO	BBO	IBA	WOA	SCA	SSA
1	476.80	461.20	496.05	525.80	518.60	530.0	481.60	471.60
5	356.65	340.75	350.80	365.75	370.80	402.65	360.50	342.95
10	295.40	310.90	308.50	310.95	340.95	338.70	334.85	289.45
15	277.25	283.20	282.80	290.20	310.10	308.60	308.20	273.40
20	276.85	280.45	276.40	279.50	296.40	299.65	293.80	271.25
25	275.10	277.30	273.70	268.15	294.10	290.20	289.40	269.85
30	274.85	275.65	271.65	258.90	292.45	285.60	286.00	269.10
35	274.40	274.00	270.00	257.40	291.60	282.25	284.45	268.55

the route obtained by SSA has slightly more cost than the recently reported data [20]. However, after combining the overall effect of time and cost trade-off, it is realized that the time required in SSA is significantly less compared to other algorithms and thus accounts for the slightly higher cost and outperforms all other algorithms. So it becomes evident that SSA has the most superior performance than all other algorithms for fast, real-time, and optimal route re-planning.







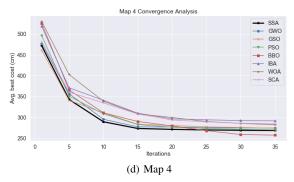


Fig. 8: Convergence Curve of Different Maps

The simplicity, flexibility and gradient-free mechanism of the SSA make it immune to local optima stagnation and thereby improving the speed of convergence and making it suitable for the route planning and various other optimizations problems in real-life.

Future work may be focussed on extending this work by constructing an environment which better mimics a real-world scenario by introducing dynamic obstacles which, along with priority assignment associated with the goals and some hardware related constraints like minimum turning radius or maximum pitch angles should also be considered. A hybrid or a modified algorithm based on SSA for route planning and other real-world problem can be proposed to enhance the performance even further.

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