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Three Dimensional multi-UAV path planning using Modified Grey Wolf Optimizer

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Abstract— Robot path planning is a task to determine the most feasible path between origin and destination while avoiding collisions in the underlying environment. This task has always been characterized as a high dimensional optimization problem and is considered NP-Hard. Numerous algorithms have been proposed that provide solutions to the problem of path planning in a deterministic and non-deterministic way. However, the problem is open to new algorithms that have the potential to obtain better quality solutions with less time complexity. This paper presents a new approach to solve the problem of three-dimensional path planning of a flying vehicle while maintaining a safe distance from obstacles on the road. A new approach based on the modified grey wolf optimization algorithm is applied to the problem. The modified algorithm is compared to the standard GWO algorithm and have shown good results.

Keywords—Grey Wolf Optimizer, GWO, Path Planning.

I. INTRODUCTION

Modern robots are good at performing complex tasks on their own, which typically require human support. Some of the recent developments, such as the Mars Spirit robot and self-driving cars [1], are an excellent example of current technological advances in the field of mobile robots. Today's robots are extremely intelligent and are able to find their own way to complete the task assigned to them. The most important tasks of mobile robots are to move from one place to another safely without damaging themselves or their corresponding environment.

The task of finding a safe path from an origin and a destination for a mobile robot is known as robot path planning. Path planning is performed through robot by designing a strategy for its movement of the robot, avoiding obstacles in the environment and reaching its goal safely. Path planning is necessary for all types of robots in different terrains such as air, water and land. Terrestrial robots are generally confined to 2D space, while air and water robots have the ability to move in three dimensions. The three-dimensional route planning is to generate an optimal path between a point of origin and a destination point, avoiding obstacles in the environment where the robot is free to change position in any direction.

Unmanned aerial vehicles (UAV) operate in the air to complete complex tasks such as surveillance, load drops, etc., and are deployed in areas where human operations are difficult. UAVs require an air route from the points of origin and destination and therefore fall within the 3D path planning domain. Three-dimensional route planning can be defined as an NP-Hard problem and the main goal is to generate an optimized route between a point of origin and a destination point. The path takes the form of a set of coordinate points very close to each other and forms a path connected as an optimized path. The 3D path planning algorithms for mobile robots include the one based on the visibility graphics [3], the random scanning algorithms [3], the maps of probabilistic paths [3], the deterministic search algorithms such as the Dijkstra algorithm, heuristic search algorithms such as A *, D * [3] and different meta-heuristic algorithms. In this study, solution of robot 3D path planning
is proposed using grey wolf optimizer based approach.

The remaining paper is organized as follows: Section II presents the related work in the field of robot path planning. The mathematical formulation of 3D path planning problem is presented in Section III. The proposed algorithm is presented in Section IV. Experimental results are reported and discussed in Section V. Finally, Section VI conclude this study and provide future directions.

II. RELATED WORK

There are several path planning solutions in the literature that use a meta-heuristic algorithm to generate the workable path between the source and destination in the search space. The main specialty of these algorithms is that they generate near optimal paths in a complex environment, while they take much less time than normal deterministic algorithms. These algorithms are very robust with a large application domain and generate good quality solutions for different types of problems. Several algorithms have been applied previously for the three-dimensional UAV path planning problem. The authors of [18] applied the A * algorithm and proposed a route planning method for UAVs. The authors of [4, 17] proposed a 3D path planning algorithm using the particle swarm optimization (PSO) algorithm. The authors of [19] used genetic algorithm (GA) to solve the problem of 2D path planning, while in [5] GA is used to solve the 3D path planning problem with multiple restrictions. In [20] a different variant called hybrid GA of multiple populations has been applied to the problem of planning the UAV path. The authors of [6] compared the GA parallel to the PSO algorithm in the problem of planning the 3D path in real time. [7] proposed Predator-Prey Pigeon based optimization approach for planning 3D UAV routes and comparing them with state of the art algorithms. The algorithm's performance was also verified in the dynamic environment in [8] and yields good results. In [9], the authors analyzed different bio-inspired algorithms for various unmanned aerial vehicle concepts related to the planning of individual and multiple UAV paths. In [22], researchers applied GWO algorithm for multi-UAV path planning and also shown significant comparison between many meta-heuristic algorithms. The nature-inspired optimization based approaches have shown good performance in solving real world optimization problems [23, 24].

III. PROBLEM FORMULATION

The multi-UAV 3D path planning is defined as a function of source and goal points that finds trajectories.

$$f(a_s, b_s, c_s, \theta_s, \psi_s) \xrightarrow{Traj_i} f(a_g, b_g, c_g, \theta_g, \psi_g) \quad (1)$$

Where (as,bs,cs) denotes the start state of the ith UAV represented as UAVi, (ag,bg,cg) denotes the goal state of the UAVi and Traji denotes the suitable collision free trajectory for UAVi in three dimensional space. Here θ_s, θ_g and ψ_s, ψ_g are the rotational unit vectors of source and goal positions of the UAV.

The main purpose of path planning is to find an optimal path, with collision-free and minimal path length cost. The initial position matrix for *n* UAVs is defined as follows:

$$p = \begin{bmatrix} p_1^1 & p_2^1 & \dots & p_n^1 \\ p_1^2 & p_2^2 & \dots & p_n^2 \\ \dots & \dots & \dots & \dots \\ p_1^m & p_2^m & \dots & p_n^m \end{bmatrix} \quad (2)$$

Where p_i represents the position of i^{th} UAV in *m* dimensional space. As we are using 3D space, so $m = 3$. The task is to reduce path length for each given UAV by following objective function:

$$(\sigma_1^*, \sigma_2^*, \dots, \sigma_n^*) = \arg\min_{\sigma_1, \sigma_2, \dots, \sigma_n} \sum_{j=1}^{n} c_j \sigma_j \quad (3)$$

Subject to constraint:

$$\varphi_{ij}(\sigma_i, \sigma_j) = 0 \quad \forall i, j = 1, 2, \dots, n$$

Where *i* and *j* represents the different UAVs. σ_i denotes the trajectory of the ith UAV and c_j denotes the cost incur to reach to goal from source.

IV. GWO ALGORITHM

The grey wolf optimization algorithm (GWO) was developed by Mirjalili et. al. in 2014 [21]. The main motivation of the GWO algorithm is the social leadership and hunting behaviour of grey wolves. The grey wolves lives in a pack of 10-12 individuals. The leader of the pack is alpha wolves which take all the decisions. Alpha wolves are followed by beta, delta and omega wolves in the social hierarchy. Beta wolves are dominated by alpha but dominate delta and omega. Similarly, the delta wolves are dominated by alpha and beta but dominates omega wolves. Another interesting mechanism of grey wolves is their hunting strategy that includes encircling, harassing, and attacking the prey. The hunting strategy of grey wolves are mathematically modelled as follows [21]:

$$D = |C * X_p(i) - X(i)| \quad (4)$$

$$X(i+1) = X_p(i) - A * D \quad (5)$$

Where *i* indicates the current iteration, *A* and *C* are coefficient vectors, X_p is the position vector of the prey, and *X* indicates the position vector of a grey wolf. Here, * is the element by element multiplication operator.
The vectors *A* and *C* are calculated as follows:

$$A = 2 * a * r_1 - a \quad (6)$$

$$C = 2 * r_2 \quad (7)$$

Where components of a are linearly decreased from 2 to 0 over the course of iterations and can be presented as follows:

$$a = 2\left(1-\left(\text{iter} / \text{Max\_iter}\right)\right) \tag{8}$$

r_1, r_2 are random vectors in [0, 1].

Hunting Behaviour:

Grey wolves have the ability to recognize the location of prey and encircle them. The hunt is usually guided by the alpha. The beta and delta might also participate in hunting occasionally. However, in an abstract search space we have no idea about the location of the optimum (prey). In order to mathematically simulate the hunting behaviour of grey wolves, we suppose that the alpha (best candidate solution) beta, and delta have better knowledge about the potential location of prey. Therefore, we save the first three best solutions obtained so far and oblige the other search agents (including the omegas) to update their positions according to the position of the best search agents. The following equations are proposed in this regard.

$$D_{alpha} = \left|C_1 * X_{alpha} - X\right| \tag{9}$$

$$D_{beta} = \left|C_2 * X_{beta} - X\right| \tag{10}$$

$$D_{delta} = \left|C_3 * X_{delta} - X\right| \tag{11}$$

$$X_1 = X_{alpha} - A * D_{alpha} \tag{12}$$

$$X_2 = X_{beta} - A * D_{beta} \tag{13}$$

$$X_3 = X_{delta} - A * D_{delta} \tag{14}$$

$$X(i+1) = \left(X_1 + X_2 + X_3\right)/3 \tag{15}$$

V. PROPOSED MODIFIED GWO ALGORITHM

The proposed changes in GWO are as follows:

$$a = 2(1-((iter)^2/(iter_{\max})^2)) \tag{16}$$

The proposed change in the calculation of a results in better trade-off between exploration and exploitation. Previously, the value of a is linearly decreasing, however, in the proposed MDGWO algorithm, the a is non-linearly decreased which provides more exploration in the initial iterations.

We have applied the proposed MDGWO algorithm in multi-UAV for finding the path from source to goal for each UAV For optimizing criterion given in Eq. (3) which gives better results as compared to the original GWO algorithm.

5.1 Algorithm:

Algorithm 1 Algorithm for multi-UAV path planning using MDGWO.

```
Initialize parameters: pop. size: n, initial position, max iterations: iter_max, a, A, C.
Calculate the fitness value of each UAV.
    (a) X_alpha = the best search agent
    (b) X_beta = the second best search agent
    (c) X_delta = the third best search agent
while iter < iter_max do
    for all (i = 1 to n) do
        Update positions of the current UAVs.
    end for
    Update a, A and C according to the equation (16), (6) and (7).
    Calculate the fitness of all the UAV.
    Update X_alpha, X_beta and X_delta using the equation (12), (13) and (14).
    iter = iter + 1.
end while
Output the best grey wolf (X_alpha) solution as the most suitable path.
```

5.2 Map Description:

The map describes the workspace in which UAV to be operated. Table 1 represents boundary Information of three maps. Table 2 represents the start and end position of each UAV. This map consists of obstacles and free space. Table 3 denotes the presence of obstacles in the map. Each UAV finds the trajectory in the free space avoiding any type of conflicts. The description is given in following tables:

Table 1: 3D map Boundary Information.

Map	**Start Boundary**	**End Boundary**
Map 1	(0, -5,0)	(10,20,6)
Map 2	(0,0,0)	(20,5,6)
Map 3	(0, -5,0)	(10,20,6)

Table 2: 3D map Start and Goal Information.

Map	**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)}

VI. RESULTS AND DISCUSSION

The algorithm is implemented for the path planning in the 3D environment. The experimentation is done in MATLAB 2009a in a PC with CPU of 3.4 Ghz and a 2 GB RAM. The algorithm is run in the environment described in the previous section. Three different maps are chosen for the algorithm to be tested demonstrated in Fig 4 a), b) and c) respectively. The initial parameters taken are defined as follows:

1. Population Size: 20-30
2. Number of iterations: 25-50
3. Initial *a* value: 2

The algorithm is run on three distinct maps and then the results are tested and compared with GWO algorithm. The generated paths for all the maps is shown from Fig. 1-6, while the average running time with the number of iterations for the meta-heuristic algorithms and the GWO algorithms are presented in Table 4, Table 5, and Table 6 for Map 1, 2, and 3, respectively. From the Table 4, 5, and 6, it has been observed that the total best cost result of the UAVs and the time taken for the proposed algorithm is less as compared to GWO algorithm. We have found the best cost of each UAV after running the simulation many times. The population size and Iteration is chosen in such a way to manage the best exploration and exploitation phase of the algorithm. The reason behind the better performance of the proposed algorithm as compared to standard GWO is the better trade-off between exploration and exploitation phenomenon.

Table 3: 3D map Obstacle Information

Algo	Pop. Size	Itera tions	Best Cost					Time
			UAV_1	UAV_2	UAV_3	UAV_4	UAV_5	
GWO	20	25	213	300	355	274	94	92.46
mGWO	20	25	273	338	341	370	94	89.62
GWO	25	40	225	312	339	254	92	104.87
mGWO	25	40	199	314	347	250	94	95.16

Table 4: Running time of algorithms for Map 1 for different population count and iterations

Obst. No.	Map 1	Map 2	Map 3
1	(0,2,0) - (10,2,5,1.5)	(3.1,0,2.1) – (3.9,5,6)	(0,2,0) - (10,2,5,1.5)
2	(0,2,4.5) - (10,2.5,6)	(9.1,0,2.1) – (9.9,5,6)	(0,2,4.5) - (10,2.5,6)
3	(0,2,1.5) - (3,2.5,4.5)	(15.1,0,2.1) – (15.9,5,6)	(0,2,1.5) - (3,2.5,4.5)
4	(7,2,1.5) - (10,2.5,4.5)	(0.1,0,0) – (0.9,5,3.9)	(7,2,1.5) - (10,2.5,4.5)
5	(3,0,2.4) - (7,0.5,4.5)	(6.1,0,0) – (6.9,5,3.9)	(3,0,2.4) - (7,0.5,4.5)
6	(0,15,0) - (10,20,1)	(12.1,0,0) – (12.9,5,3.9)	(0,15,0) - (10,20,1)
7	(0,15,1) - (10,16,3.5)	(18.1,0,0) – (18.9,5,3.9)	(0,15,1) - (10,16,3.5)
8	(0,18,4.5) - (10,19,6)	NA	(0,18,4.5) - (10,19,6)
9	NA	NA	(0,-2,0) – (10,-1.5,1.5)
10	NA	NA	(0,-2,3) – (10,-1.5,5.5)
11	NA	NA	(0,7,0) – (10,7.5,0.5)
12	NA	NA	(0,7,2) – (10,7.5,5.5)
13	NA	NA	(0,11,0) – (10,11.5,2.5)
14	NA	NA	(0,11,4) – (10,11.5,5.5)
15	NA	NA	(0,-2,1.5) – (3,-1.5,3)
16	NA	NA	(6,-2,1.5) – (10,-1.5,3)

Table 5: Running time of algorithms for Map 2 for different population count and iterations

Algo	Pop. Size	Iterations	Best Cost					Time UAV_1
			UAV_1	UAV_2	UAV_3	UAV_4	UAV_5	
GWO	20	25	207	308	GWO	20	25	207
mGWO	20	25	203	306	mGWO	20	25	203
GWO	25	40	191	298	GWO	25	40	191
mGWO	25	40	197	292	mGWO	25	40	197

Table 6: Running time of algorithms for Map 3 for different population count and iterations.

Algo	Pop. Size	Iterations	Best Cost					Time
			UAV_1	UAV_2	UAV_3	UAV_4	UAV_5	
GWO	20	25	321	381	317	353	423	139.78
mGWO	20	25	341	309	293	327	345	135.86
GWO	30	40	319	313	315	333	345	135.90
mGWO	30	40	279	345	311	353	321	134.42

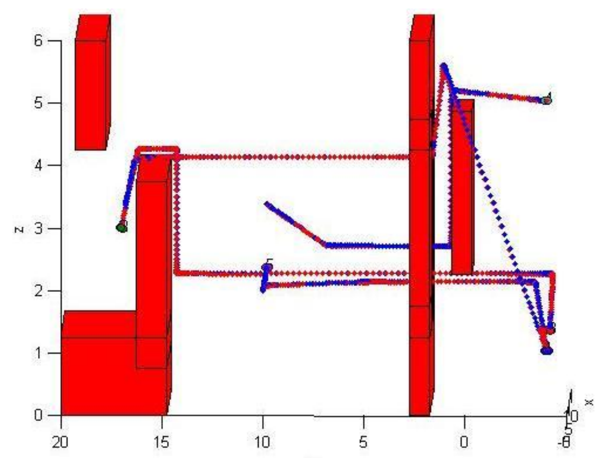

Fig 1: Trajectory generated for Map 1 using MDGWO algorithm for pop. Size 20, and iterations 25.

The simulation for path planning of multiple UAVs are presented from Fig. 1-6. Here, red line represents the estimated path *pf* and the blue line represents the path that UAV actually traverse in the workspace.

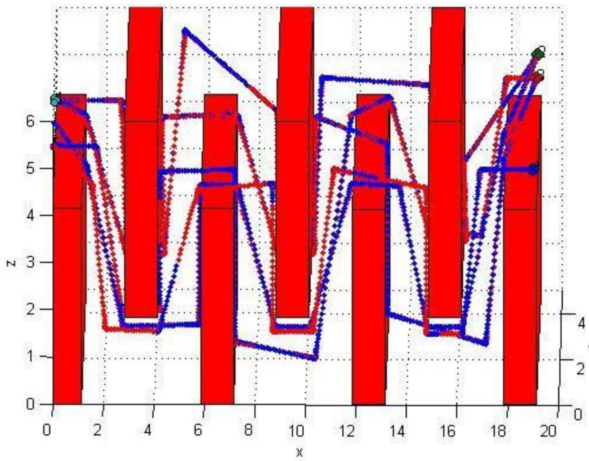

Fig 2: Trajectory generated for Map 2 using MDGWO algorithm for pop. Size 20, and iterations 25.

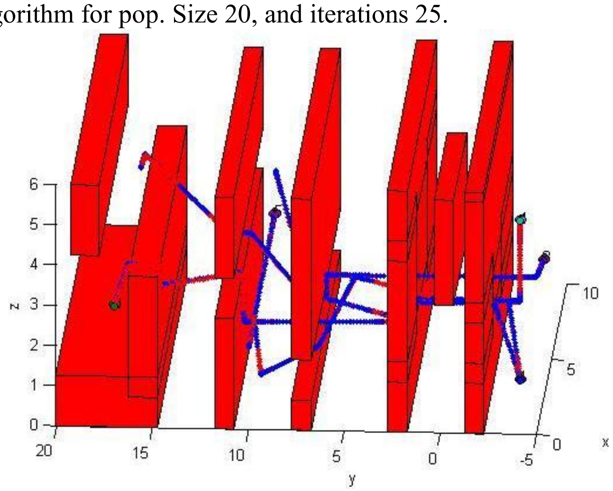

Fig 3: Trajectory generated for Map 3 using MDGWO algorithm for pop. Size 20, and iterations 25.

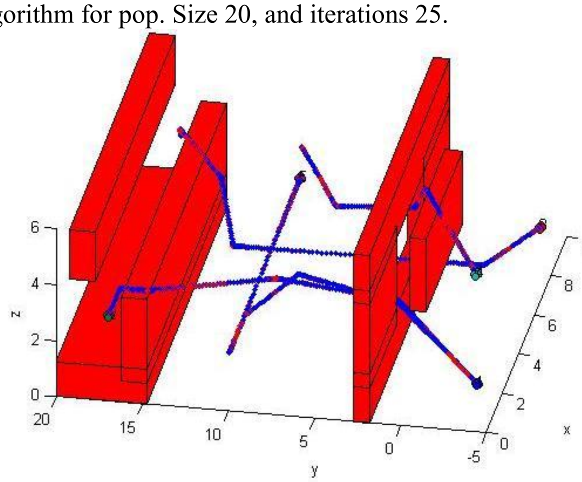

Fig 4: Trajectory generated for Map 1 using MDGWO algorithm for pop. Size 25, and iterations 40.

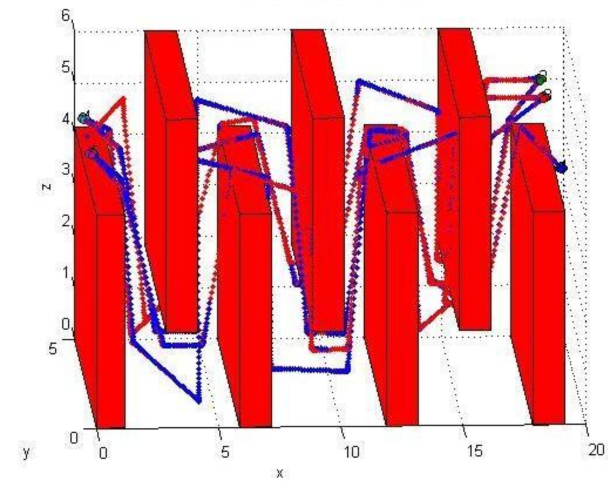

Fig 5: Trajectory generated for Map 2 using MDGWO algorithm for pop. Size 30, and iterations 40.

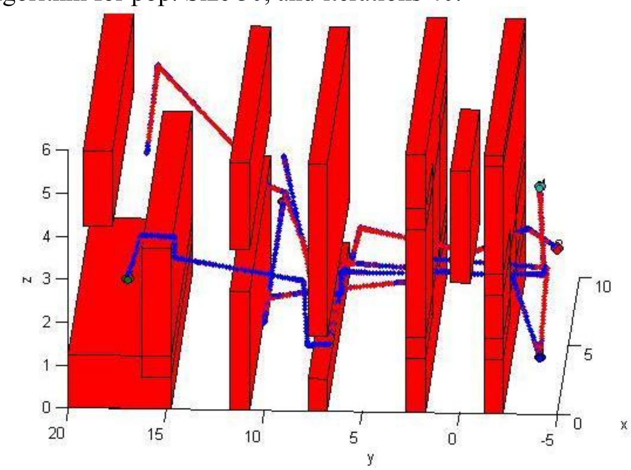

Fig 6: Trajectory generated for Map 3 using MDGWO algorithm for pop. Size 25, and iterations 40.

VII. CONCLUSION AND FUTURE SCOPE

The document presents a modified GWO algorithm for planning 3D UAV paths. The algorithm successfully generates an optimized route between the source and destination, while maintaining optimal flight restrictions. The MDGWO algorithm improves its exploration and exploitation features and helps the algorithm achieve better results and faster convergence. As a consequence, the cost of the route is lower and obstacles are avoided during its execution and, therefore, the algorithm shows promising results after the comparison of the GWO algorithm. The new approach is more explorative and during many iterations, it has been observed that the algorithm leaves the local optimum and the solution is further improved by adding the mutation to the route generation algorithm. The new algorithm shows a good potential solution for the implementation of the search for the path of a UAV in real time in the presence of static obstacles along the way.

The future work for this study would be to add different dynamic features to the 3D map in the form of dynamic obstacles to implement the path rescheduling algorithm, which is an extremely important field for the robot path planning domain. The algorithm can also be implemented for route planning and assignment of multi-UAV 3D tasks as a future research task.

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