Optimization Techniques for Multi Cooperative Systems MCTR 1021
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Joint Optimisation of Multi-UAV Target Assignment and Path Planning

By

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List of Abbreviations

UAVs	Unmanned Aerial Vehicles
GB-SMO	Gradient-Based Sequential Minimal Optimization
RSUs	Roadside Units

Chapter 1

Literature Review

In [1], Ma et al. attacked the Multi-UAVs to Multi-tasks assignment and path planning problem. They considered this problem as a multi-Traveling Salesman Problem (MTSP), which is considered an NP-hard problem. Genetic algorithm (GA), a meta-heuristic technique used in solving the MTSP problem, performs less efficiently for a large scale MTSP problem. Moreover, GA requires the number of UAVs to be known in advance. For this, [1] proposed coordinated optimisation algorithm combining GA with cluster to determine the minimum number of UAVs needed to finish the entire task. Then, the task assignment and the path planning problem given a specified number UAVs are simultaneously resolved.

Dewangan et al. approached the multi-UAV 3D path planning problem using the Grey wolf optimization (GWO) technique [2]. Their objective was to minimise the path length for each UAV, where each UAV has a unique target. The path planning should be conducted such no collisions occur among the UAVs along with no collisions with obstacles. They used 3D discrete grid maps as the workspace for the UAVs, such that there are six possible directions that the UAV can move towards at a particular point. The GWO technique was tested against multiple other techniques and proved to be an effective solution that is acquired in a minumum time.

Liu et al. in [3] designed and implemented an Improved Life-Cycle Swarm Optimisation (ILSO) Algorithm and the varying of the population was practised and further combined with Rapid exploring Random Tree (RRT) to acquire an optimised path for task allocation and trajectory planning in three-dimensional complex terrain for a Multi-UAV in Combat Mission Planning. The improved algorithm was then compared with Particle Swarm Optimization (PSO) and Whaled Optimization Algorithm (WOA).

Wu et al. in [4] designed a Bi-directional adaptive A* algorithm to enhance the efficiency of expansion process and ensure the smoothness of the path compared to the conventional A*. The adaptive strategies conducted were Adaptive Step and Adaptive Weight strategies. The simulation of the UAV path planning under multiple constraints was carried out to show the superiority of Bi-directional A* in run time and path quality.

Bai et al. [5] proposed a multi-UAV cooperative trajectory planning model based on many-objective optimization to reduce the costs associated with UAV trajectory distance, time, threat, and coordination. In order to increase the model's solution effectiveness and hasten the algorithm's convergence, their research additionally developed a segmented crossover approach and added a dynamic crossover probability to the crossover operator. The multi-UAV cooperative trajectory planning algorithm was effective, meeting a variety of real needs, according to experimental data.

Zhang et al. [6] developed the Multi-objective particle swarm optimization algorithm with reinforcement learning-based multimodal cooperation (MCMOPSO-RL) to find optimal paths by solving constraints. A multi-mode collaborative strategy to update particle positions, where three modes have been developed to balance population diversity and convergence speed, including exploration, exploitation and update modes hybrid was designed. The experimental results show that MCMOPSO-RL can solve the trajectory planning problem for multiple UAVs more efficiently and robustly than other algorithms.

For multi-UAV job allocation, Shi et al. [7] proposed a better bat optimization algorithm. The calculation of the drone's flight distance and the comparison of the number of drones and target points are added using the bat algorithm. According to the experimental findings, the modified algorithm can shorten the UAV's flight distance while also reducing calculation time and flight time and increasing algorithm efficiency.

In [8], the challenge problem of multi-UAV trajectory planning has been solved. The Gradient-Based Sequential Minimal Optimization (GB-SMO) is used to decouple the mutual collision cost, which reduces the computational complexity from O(n2) to O(n) in each iteration. Compared with the coupled method, the proposed method is efficient for a large number of quadrotors. The outdoor experiments further prove that the proposed method performs well in the formation rendezvous and formation reconfiguration task and can plan smooth and collision-free trajectories for the multi-quadrotor system efficiently.

In addition, [9] introduced findings on the path planning problem for multiple Unmanned Aerial Vehicles (UAVs) for collecting data from a number of pre-deployed Roadside Units (RSUs) considering several scenarios. We assume that the battery capacity of a UAV and/or mission time are not adequate to visit all RSUs. We therefore formulated two problems: one assumes that each UAV has similar travel distance, while the other aims to optimize total path length. To solve these problems, we propose two modified metaheuristic-based approximate solutions with different evolutionary operators. Our results show that the proposed HS algorithm outperforms the GA in terms of cost-effectiveness when the problem becomes more complicated, and in convergence time when the search process is relatively straightforward.

In [10], Qie et al. proposed a simultaneous target assignment and path planning (STAPP) algorithm for multi-UAVs. Their approach focused on a 2D workspace where each target is assigned to one and only one UAV and the planned path must account for no collisions with other UAVs and no passing through threat areas. Reinforcement learning was used for solving the problem where they measured the training effectiveness with indicators including collision rate among agents in addition to with threat areas, task completion rate etc.

Chapter 2

Problem Formulation

The UAVs are given an initial position where each UAV can be given a set of targets that should be reached by the UAV. The problem is considered as Multi Travelling Salesman Problem (MTSP). A set of obstacles is given where the UAVs are required to not collide with them. All UAVs are assumed to be on different elevations such that they do not collide with themselves. The obstacles are supposed to span the whole height of the map. A scenario can be seen n Figure 2.1.

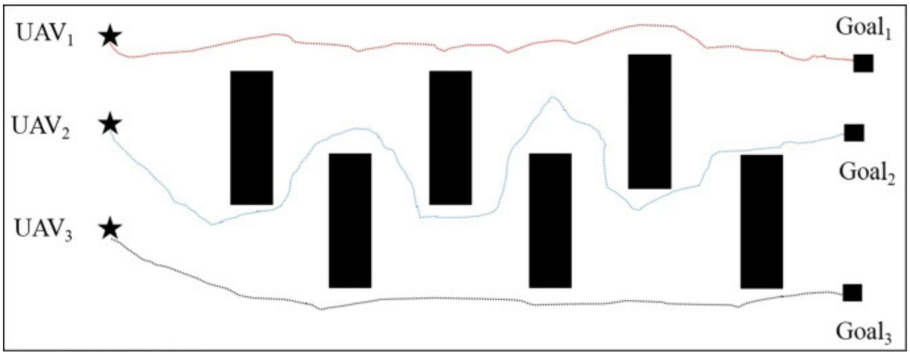

Figure 2.1: A path planning scenario showing three UAVs assigned to three tasks. [2]

2.1 Objective Functions and Decision Variables

The decision variables accounted for in this formulation are as follows.

1. Number of UAVs deployed n_k
2. Number of total tasks T_{tot}
3. The assigned tasks for each UAV T_k

Two objective functions are used in this problem optimisation. The first objective function is minimising the total distance taken by all UAVs, such that D is the total path length covered by all UAVs as shown below.

$$D = \sum_{j=1}^{k} \sum_{i=0}^{n_k} d_{i,i+1}, \tag{2.1}$$

where k is the number of UAVs, n_k is the number of tasks for UAV k, $x_{i,i+1}$ is the distance between task i and $i + 1$, and task 0 is the initial UAV position.

The second objective function to minimise the number of UAVs k that are assigned to tasks in the workspace.

The cost function can then be calculated using the following equation.

$$J = \omega_1 D + \omega_2 k, \tag{2.2}$$

such that ω is a weight to normalise the costs. We can then optimise using the following

$$\arg\min f(n_k, t_{tot}, T_k) \tag{2.3}$$

2.2 Constraints

The following constraints must be considered:

1. UAVs have to avoid obstacles.
2. Max number of tasks per UAV $n_k \leq TA$, where TA is the maximum number of tasks that can be assigned for each UAV.
3. Maximum time elapsed by each UAV to finish its tasks $T_{el} \leq T_{max}$, where T_{max} is the maximum time that is elapsed for the whole process duration.

2.3 Assumptions

The following assumptions are made to simplify the problem:

1. All UAVs have the same velocity.
2. The environment is static and does not change with each run.
3. All UAVs have different starting elevations and can not change said elevation. (cannot collide with themselves)
4. Obstacles span the entire height of the map.

Chapter 3

Optimization Techniques

3.1 Genetic Algorithm

3.1.1 Task Assignment GA

The main parts that affect the performance of GA in Task assignment problem is how to crossover between two parents, how to mutate, and the selection of the parents of the crossover and the mutation. And, in our part, we split the generation to elite, crossover, and mutate. We passed the most elite children to the next generation (who have the best fitness), and we decided to crossover between the most elite parent, and the second parent is chosen in a consecutive way depending on the fitness, i.e. (1,2), then (1,3), then (1,4),... etc.
and we cross over by taking a task from a specific UAV from parent 2, and assign it to the same UAV in the child 1, but child 1 has all the other tasks as parent 1, and vice versa. Child 2 has all same tasks from parent 2 except 1 task from parent 1 for a specific UAV.
In addition, the mutation process is done to the worst parents, by swapping tasks of 2 random UAV for that parent.

3.1.2 Case Studies

The same four test cases will be used in GA algorithm, and the same 4 test cases will be used for both the task assignment and the path planning.

Case Study #	UAVs Number	Tasks Number	Map Size	n_{pop}	n_{gen}
1	5	5	10*10	50	100
2	10(y-axis)	15(random)	100*100	50	100
3	10(random)	15(random)	100*100	100	150
4	50	70	1000*1000	100	200

Table 3.1: Genetic algorithm parameters per case study for Task Assignment and Path Planning

p_{elite}	$p_{crossover}$	$p_{mutation}$	$parents_{selection}$	$mutation_{selection}$
0.1	0.8	0.1	”SUS”	”Worst”

Table 3.2: Other Genetic algorithm parameters

Test Case 1

The first test case is a simple one and will be in 10*10 map. We have 5 UAVs at positions (0,2), (0,1), (1,8), (1,6), (2,1). In addition, we have 5 tasks to be assigned in positions (2, 5), (1, 7), (6, 2), (5, 9), (1, 1) like in Fig **??**

Test Case 2

The second test case is a little more complex and will be in 100*100 map. We have 10 UAVs on the y-axis. In addition, we have 15 tasks to be assigned in random positions

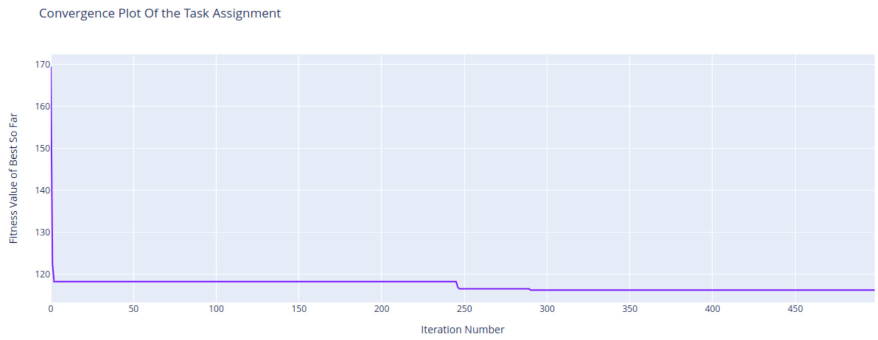

Figure 3.1: Test Case 1: The Task Assignment convergence plot

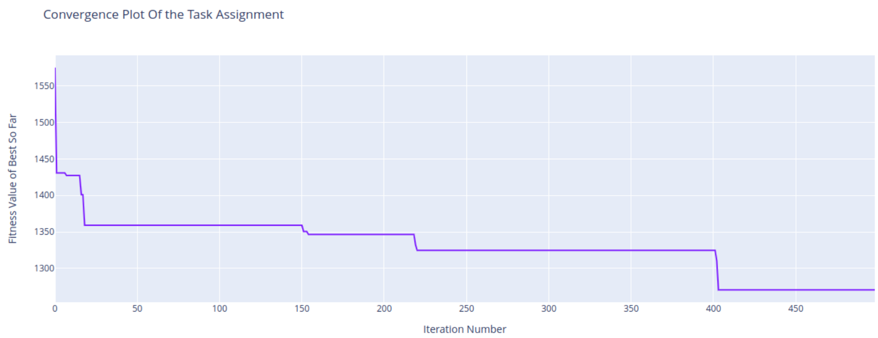

Figure 3.2: Test Case 2: The Task Assignment convergence plot

Test Case 3

The third test case is the same of the second one and will be in 100*100 map. We have 10 UAVs, but in random position in the map. In addition, we have 15 tasks to be assigned in random positions

Test Case 4

The last test case is the more realistic one and will be in 1000*1000 map. We have 50 UAVs on the x-axis. In addition, we have 70 tasks to be assigned in random positions .

3.1.3 Results and Discussion

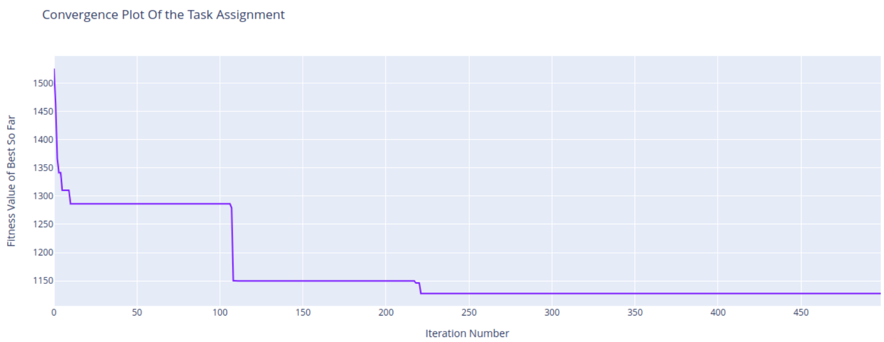

Figure 3.3: Test Case 3: The Task Assignment convergence plot

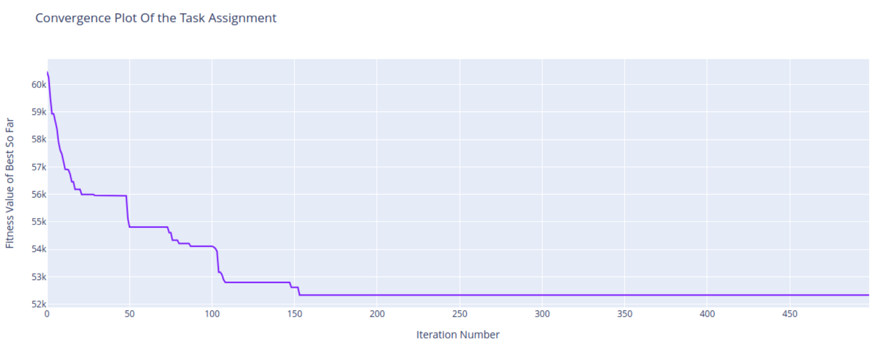

Figure 3.4: Test Case 4: The Task Assignment convergence plot

Bibliography

[1] Yunhong Ma, Heng Zhang, Yaozhong Zhang, Ruizhou Gao, Zhao Xu, and Jie Yang. Coordinated optimization algorithm combining ga with cluster for multi-uavs to multi-tasks task assignment and path planning. In *2019 IEEE 15th International Conference on Control and Automation (ICCA)*, pages 1026–1031. IEEE, 2019.

[2] Ram Kishan Dewangan, Anupam Shukla, and W Wilfred Godfrey. Three dimensional path planning using grey wolf optimizer for uavs. *Applied Intelligence*, 49(6):2201–2217, 2019.

[3] Haishi Liu, Qiyong Chen, Nan Pan, Yuxuan Sun, and Yaluo Yang. Three-dimensional mountain complex terrain and heterogeneous multi-uav cooperative combat mission planning. *IEEE Access*, 8:197407–197419, 01 2020.

[4] Wu Xueli, Xu Lei, Zhen Ran, and Wu Xiaojing. Bi-directional adaptive a* algorithm toward optimal path planning for large-scale uav under multi-constraints. *IEEE Access*, PP:1–1, 04 2020.

[5] Hui Bai, Tian Fan, Yuan Niu, and Zhihua Cui. Multi-uav cooperative trajectory planning based on many-objective evolutionary algorithm. *Complex System Modeling and Simulation*, 2(2):130–141, 2022.

[6] Xiangyin Zhang, Shuang Xia, Xiuzhi Li, and Tian Zhang. Multi-objective particle swarm optimization with multi-mode collaboration based on reinforcement learning for path planning of unmanned air vehicles. *Knowledge-Based Systems*, 250:109075, 2022.

[7] Jiaqi Shi, Li Tan, Xiaofeng Lian, Xinyue Lv, and Tianying Xu. Multi-uav task allocation method based on improved bat algorithm. In Xingming Sun, Xiaorui Zhang, Zhihua Xia, and Elisa Bertino, editors, *Artificial Intelligence and Security*, pages 205–213, Cham, 2021. Springer International Publishing.

[8] Qiaoyang Xia, Shuang Liu, Mingyang Guo, Hui Wang, Qigao Zhou, and Xiancheng Zhang. Multi-uav trajectory planning using gradient-based sequence minimal optimization. *Robotics and Autonomous Systems*, 137:103728, 2021.

[9] Hamidullah Binol, Eyuphan Bulut, Kemal Akkaya, and Ismail Guvenc. Time optimal multi-uav path planning for gathering its data from roadside units. In *2018 IEEE 88th Vehicular Technology Conference (VTC-Fall)*, pages 1–5. IEEE, 2018.

[10] Han Qie, Dianxi Shi, Tianlong Shen, Xinhai Xu, Yuan Li, and Liujing Wang. Joint optimization of multi-uav target assignment and path planning based on multi-agent reinforcement learning. *IEEE access*, 7:146264–146272, 2019.