Multi-UAV Path Planning with Genetic Algorithm

Mingyu Li[†*], Pei-Fa Sun[*], Sang-Woon Jeon[*], Xiaoyan Zhao[†], Hu Jin[*]
[†] College of Computer and lnformation Engineering, Henan Normal University, Xinxiang, China
[*] Department of Electrical and Electronic Engineering, Hanyang University, Ansan, South Korea
e-mail:{liminygu, pfsun, sangwoonjeon, hjin}@hanyang.ac.kr, zhaoxiaoyan@htu.edu.cn

***Abstract*—With the continuous evolution of communication technology, unmanned aerial vehicles (UAVs) are considered pivotal in 6G communications. As the number of tasks steadily increases, simultaneous path planning for multiple UAVs has emerged as an important research topic. The multi-path planning problem for UAVs is essentially a typical instance of the multiple traveling salesman problem (MTSP). Since the MTSP problem is NP-hard, the effect of using heuristic optimization algorithms will be significantly better than traditional optimization methods. To optimize the information collection process, we employ the K-means clustering method to generate relay nodes. Subsequently, a multi-UAV path planning model is constructed, and a genetic algorithm (GA) is employed to find the optimal solution. Finally, the effectiveness of the proposed GA in tackling the MTSP problem is validated through comprehensive experiments under diverse scenarios.**

***Index Terms*—Genetic algorithm, multiple traveling salesman problem, unmanned aerial vehicle**

I. Introduction

With the onset of the 6G era, unmanned aerial vehicle (UAV) technology has gained extensive utilization within communication systems across diverse operational contexts, owing to its exceptional mobility, adaptable flexibility, and low cost [1]. Notably, in the scenarios of information collection, the inherent flexibility of UAVs ensures efficient and swift task completion [2]. Simultaneously, as the volume of tasks increases, ensuring the minimum distance while accomplishing path planning for multiple UAVs has become a prominent research challenge [3]. To Address this concern, the path planning for multiple UAVs can be conceptualized as the multiple traveling salesman problem (MTSP) [4], which is a well-known category of NP-hard problems. [5]. For NP-hard problems, it is difficult to solve them using traditional mathematical calculation methods [6].

For such a problem, several researchers have applied computational intelligence (CI) to solve it. Chen *et al.* [7] proposed an improved genetic algorithm (IGA) and an ant colony algorithm based on particle swarm optimization in parallel to solve the UAV path planning problem. Zhang *et al.* [8] proposed a state transition simulated annealing algorithm (STASA) to solve the multiple traveling salesman problem. In [9], the authors proposed a new hybrid algorithm called AC2OptGA, which combines the ant colony algorithm, genetic algorithm, and 2-opt algorithm to solve the MTSP problem.

In this paper, considering the uncertainty of sensor number and their locations, we cluster the sensors based on the K-means clustering algorithm and locate a relay node at each cluster center, which collects information from nearby sensors. Then, UAVs only need to visit the relay nodes to complete information collection where the path planning for the multiple UAVs can be modeled by MTSP. Regarding such highly difficult computational challenges posed by MTSP, computational intelligence emerges as a promising solution. In response, we introduced a genetic algorithm (GA) that adeptly facilitates path planning for multiple UAVs. Our proposed algorithm takes a balance between ensuring algorithmic computational efficiency and yielding reasonable path-planning outcomes.

II. Multi-UAV Path Planning

A. Path Planning Model

Due to high energy consumption of the UAVs on flying, the primary goal of multiple UAVs in the information collection process is to shorten the flight distance as much as possible. Suppose that there are number N_s of sensors uniformly distributed within a range of $R \times R$ m^2 and they need to send their sensing information. We first adopt K-means clustering method [10] to select N_r points at which relay nodes are located to collect information from nearby sensors. Then, N_u UAVs need to visit those N_r relay nodes only to hover and obtain sensing information.

Each UAV path starts from the hub station, which is located at the center of $R \times R$ area and is denoted by index t_0, and ends at the same location. Let T_j denote the number of relay nodes that the jth UAV should visit where $j \in [1, N_u]$. If the UAVs do not visit overlapped relay nodes, we have $\sum_{j=1}^{N_u} T_j = N_r$. The objective of path planning is to minimize the cumulative distance traveled by all the UAVs while we employ GA to solve the corresponding optimization problem. In the GA, each individual within the population contains the path planning solution for all the UAVs and has a vector form of length $N_r + N_u$. Let the vector be expressed by $\vec{x} = [t_1, t_2, \ldots, t_{N_r}, T_1, T_2, \ldots, T_{N_u}]$, where t_i for $1 \leq i \leq N_r$ could be any relay node's index. For the simplicity of later description, we define $s_j = \sum_{i=1}^{j} T_i$. Our path planning $\vec{x}$ indicates that UAV j for $1 \leq j \leq N_u$ sequentially visits the relay nodes with indexes $t_{s_j - T_j + 1}, ..., t_{s_j}$. If $d(i, k)$ denotes the distance between the two relay nodes i and k, the flight distance of UAV j can be obtained as

$$D_j = d(t_0, t_{s_j - T_j + 1}) + \sum_{i = t_{s_j - T_j + 1}}^{t_{s_j - 1}} d(t_i, t_{i+1}) + d(t_{s_j}, t_0). \quad (1)$$

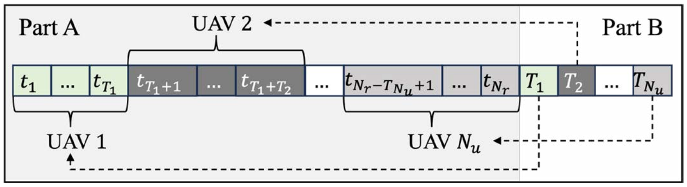

Fig. 1. Graphical explanation of each individual.

Consequently, the objective function could be expressed as

$$
\begin{aligned}
&\min_{\vec{x}} f(\vec{x}) = \sum_{j=1}^{N_u} D_j \\
s.t.\ &C1: \ \sum_{j=1}^{N_u} T_j = N_r, \\
&C2: \ T_j > 0, \ 1 \leq j \leq N_u, \\
&C3: \ t_1 \neq t_2 \neq \cdots \neq t_{N_r}.
\end{aligned} \tag{2}
$$

B. The Proposed Genetic Algorithm

Initialization: The optimization goal of this paper is to minimize the total path length of all the UAVs. We generate a population of M individuals according to the optimal objective. Each individual vector $\vec{x}$ has N_r+N_u genes (or elements), representing a path-planning solution. Individuals need to go through selection, crossover, and mutation processes separately to calculate the fitness value (or equivalently the total path length). We read each individual by two parts based on the different contents. As shown in Fig. 1, the first N_r genes, denoted by part A, represent the relay node indexes, while the last N_u genes, denoted by part B, represent the number of relay nodes that each UAV visits. In the process of algorithm evolution, these two parts evolve simultaneously.

Selection: We use the roulette wheel operator for the selection process. Selection is the process of selecting better individuals from the old population to form a new population. According to the objective function, if an individual's fitness value is smaller, the probability of being selected is larger. We use f_n to represent the fitness value of individual n for $1 \leq n \leq M$, and the probability of the individual n being selected can be given by (3).

$$
P_n = \frac{f_n}{\sum_{k=1}^{M} f_k}. \tag{3}
$$

Then, a random number R_n is generated from $[0, 1]$ in a uniform manner for individual n. If R_n is smaller than P_n, individual n is selected. We use the individuals selected in the above way to replace the original individuals in the population and complete the selection process.

Crossover: The crossover process uses an order crossover operator. Given a random crossover probability P_c, if a newly generated random number R_n of individual n is less than P_c, the individual is selected to participate in the crossover process. Each individual's A and B parts will be crossed simultaneously but in different ways. The crossover process is shown in Fig. 2.

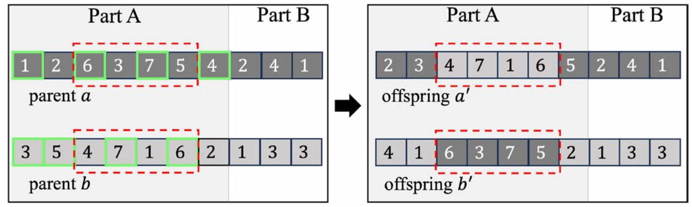

Fig. 2. Crossover process

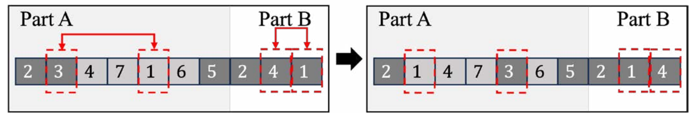

Fig. 3. Mutation process

For part A, each two parent individuals are paired, and two crossover points L_1 and L_2 for $1 \leq L_1 < L_2 \leq N_r$ are randomly selected for each pair of parent individuals. First, we take out the genes between the L_1 and L_2 of the parent a and replace them in the corresponding position of the offspring a. Then, sort the remaining genes in parent a according to the order of the relay node index in the gene of parent b. Finally, replace the sorted genes in the remaining gene positions in the offspring a'.

The generation process for offspring b' is similar to that of offspring a'. Therefore, the offspring a' is based on the parent a, and the offspring b' is generated based on the gene sequence of the parent b.

For part B, we just need to copy the parent's gene sequence to the offspring's corresponding position. Typically, two parents produce two different offspring to increase the randomness of the evolutionary process. After the crossover process, the offspring still satisfies the constraints $C1$ and $C3$.

Mutation: The central aspect of the mutation process is the mutation probability P_m. The determination of individual participation in the mutation process is similar to that of the crossover process. Determine which individuals will participate in the mutation process by comparing a randomly generated number R_n and P_m. Part A and Part B use the same mutation method.

For Part A, we randomly select two different numbers I_1 and I_2 from $[1, N_r]$ as the genes of the individual participating in the mutation process. Then, we exchange the relay node index in these two genes.

The mutation process of Part B is different from Part A in that the selection range of the genes involved in the mutation is $[1, N_u]$. Other mutation steps are identical to that of part A. An example of one mutation process is shown in Fig. 3.

After the above optimization process, the minimized multi-UAV path planning solution that satisfies all the constraints in the objective function will be obtained.

III. Experimental Results

A. Experimental Setting

In this subsection, we describe the experimental settings and the parameter configurations employed.

TABLE I
THE PARAMETER SETTINGS

Parameter	Value
Number of sensors N_s	1000
Number of relay nodes N_r	30, 40
Number of UAVs N_u	3, 4
Sensor range R	$10^4\ m$
Crossover probability P_c	0.3
Mutation probability P_m	0.1

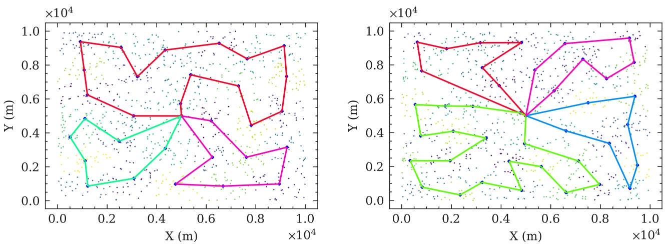

Fig. 4. Multi-path planning results for different numbers of UAVs.

As the relay nodes are generated based on the clustering of a large number of sensors, to obtain a statistically meaningful result, we generate 1000 sensors that are randomly distributed in the $R \times R$ area where $R = 10^4\ m$.

Firstly, by applying the k-means clustering method, we cluster the generated sensors. Then, multi-UAV path planning experiments are conducted based on the obtained locations of relay nodes when the numbers of UAVs and relay nodes are given. The precise parameters are outlined in Table I.

B. Discussion on the Results

Fig. 4 shows the path planning results for different numbers of UAVs. In the figure, sensors of the same color form one cluster while those relay nodes are denoted by blue color. Lines of different colors represent different flight paths of different UAVs. The left figure shows the path planning result obtained with 1800 generations when $N_u = 3$ and $N_r = 30$, while the right figure shows the result obtained with 3000 generations when $N_u = 4$ and $N_r = 40$. The experimental results show that the algorithm we proposed can find a reasonable path solution for UAVs for different numbers of UAVs and relay nodes.

Fig. 5 shows the path planning results as the generation goes over. The yellow line represents the optimal total path length, while the blue line represents the average total path length. Through comparing the experimental outcomes under different numbers of UAVs and relay nodes, we can conclude that the proposed algorithm is able to reach the minimum total path length while ensuring rational routes: no crosses among different UAV paths and satisfaction with the constraints.

IV. Conclusion

In this paper, we proposed a genetic algorithm to solve the multi-UAV path planning problem, which can be viewed as a typical MTSP. To meet the tough constraints raised by MTSP, we divided the genes in each individual in the GA population

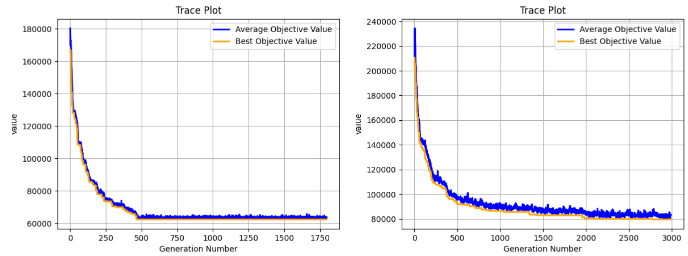

Fig. 5. Multi-path planning results over generations

into two parts according to the different purposes. In particular, those two parts have different crossover processes in the evolutionary process. Consequently, our proposed algorithm is able to minimize the total flight path length of multiple UAVs subject to constraints. Experimental results show that our proposed algorithm can obtain the optimal solution while satisfying the constraints.

In future work, we will consider the inherent characteristics of UAVs, such as battery capacity and flight costs. This will lead to a more comprehensively exploring the multi-UAV path planning problem.

Acknowledgment

This work is supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. 2022R1F1A1071093).

References

[1] B. Li, Z. Fei, and Y. Zhang, “Uav communications for 5g and beyond: Recent advances and future trends,” *IEEE Internet of Things Journal*, vol. 6, pp. 2241–2263, Dec. 2018.

[2] H. Bayerlein, M. Theile, M. Caccamo, and D. Gesbert, “Multi-uav path planning for wireless data harvesting with deep reinforcement learning,” *IEEE Open Journal of the Communications Society*, vol. 2, pp. 1171–1187, May 2021.

[3] W. He, X. Qi, and L. Liu, “A novel hybrid particle swarm optimization for multi-uav cooperate path planning,” *Applied Intelligence*, vol. 51, pp. 7350–7364, Mar. 2021.

[4] O. Cheikhrouhou and I. Khoufi, “A comprehensive survey on the multiple traveling salesman problem: Applications, approaches and taxonomy,” *Computer Science Review*, vol. 40, p. 100369, May 2021.

[5] C. H. Papadimitriou, “The euclidean travelling salesman problem is np-complete,” *Theoretical computer science*, vol. 4, pp. 237–244, Jun. 1977.

[6] Z.-H. Zhan, J. Zhang, Y. Lin, J.-Y. Li, T. Huang, X.-Q. Guo, F.-F. Wei, S. Kwong, X.-Y. Zhang, and R. You, “Matrix-based evolutionary computation,” *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 6, pp. 315–328, Jan. 2021.

[7] J. Chen, F. Ye, and Y. Li, “Travelling salesman problem for uav path planning with two parallel optimization algorithms,” in *2017 progress in electromagnetics research symposium-fall (PIERS-FALL)*, pp. 832–837, Nov. 2017.

[8] Y. Zhang, X. Han, Y. Dong, J. Xie, G. Xie, and X. Xu, “A novel state transition simulated annealing algorithm for the multiple traveling salesmen problem,” *The Journal of Supercomputing*, vol. 77, pp. 11827–11852, Mar. 2021.

[9] Y. Harrath, A. F. Salman, A. Alqaddoumi, H. Hasan, and A. Radhi, “A novel hybrid approach for solving the multiple traveling salesmen problem,” *Arab Journal of Basic and applied sciences*, vol. 26, pp. 103–112, Feb. 2019.

[10] J. A. Hartigan and M. A. Wong, “Algorithm as 136: A k-means clustering algorithm,” *Journal of the royal statistical society. series c (applied statistics)*, vol. 28, no. 1, pp. 100–108, 1979.