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Cooperative trajectory optimization for unmanned aerial vehicles in a combat environment

Tingting BAI & Daobo WANG*

School of Automation Engineering, Nanjing University of Aeronautics and Astronautics, Nanjing 211106*, China*

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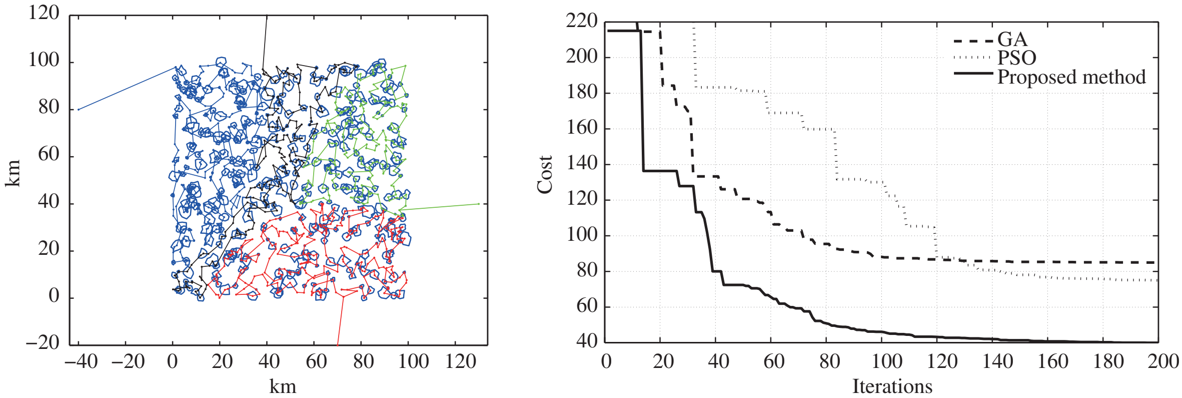
Dear editor,
Unmanned aerial vehicles (UAVs) have been widely used in both civil and military tasks. Owing to the limited payload and economic considerations, however, a single UAV is not capable of carrying out complex tasks, such as large-scale monitoring and surveillance. Therefore, a group of UAVs is usually deployed to perform these tasks. This requires the UAVs to fly over the regions of the interest, allowing the on-board sensor to detect targets [1]. To minimize the duration of the task, the flight trajectory-planning problem for a swarm of UAVs should be solved.

The multi-UAV trajectory-planning task can be considered as a multiple traveling salesman problem (MTSP), which is an extension of the classical traveling salesman problem (TSP). It is a typical N-P hard optimization problem, and meta-heuristic-based methods provide straightforward solutions to solve it. Zhang et al. [2] proposed a hybrid optimization framework, combining an adaptive ant colony algorithm with Voronoi weighted maps, to solve the optimal trajectory in the dynamic space. Li and Chou [3] proposed a novel self-adaptive learning mechanism, incorporating adaptively local searching strategies into the framework of particle swarm optimization (PSO) to determine the optimal path for mobile robots. Belkhouche [4] proposed the application of active avoidance strategies for obstacles in the environment, and determine feasible fly-zones by calculating the speed and position of the UAV relative to the obstacle; the optimal path was then obtained during subsequent processing using a genetic algorithm (GA) optimization approach. Berger et al. [5] studied the static target search task, and proposed to transform it into a linear programming problem, which significantly reduces the computational complexity and improves the efficiency of the proposed method. Hosseinabadi et al. [6] proposed a hybrid approach, combining a line-of-sight-based planner, sliding mode controller, and fuzzy strategy, to deal with the path-planning problem in an unknown environment.

Model and methodology. We assume that UAVs are flying at a constant height and speed, and therefore, a 2D Dubins model can be used to describe the motion of the UAVs. We further assume that a gimbaled installed sensor is mounted on each UAV, and thus, the sensor visibility areas would not be correlated with the attitude of the UAV. Owing to the occlusions of ground features, such as buildings and terrains, the detectable regions of each UAV at a given altitude can be determined by using a fast yet robust spatial analysis method developed in [7]. To allow the UAVs to properly detect targets, the UAVs are required, at least, to reach any point within the interior area of each polygon.

For performing cooperative surveillance path-planning for UAVs, the computational cost is vital, and thus, the application of conventional MTSP methods to the aforementioned problem may not satisfy the running time constraint. To solve with

* Corresponding author (email: dbwangpe@nuaa.edu.cn)



(a) (b)

	The cost of the resulting path			The runing time for different methods	
	Best	Worst	Average	Portion	The average running time (s)
Proposed method	3985.6	4056.2	4008.3	Clustering for depots	5.6
				TSP solver	9.2
				Total	14.8
GA	3283.4	3912.7	3694.9	Total	63.7
PSO	3379.1	4002.8	3578.3	Total	59.4

(c)

Figure 1 (Color online) (a) The resulting path obtained through the proposed algorithm; (b) comparison of the convergence for different methods; (c) comparison of the performance of different methods.

this problem, we present a hierarchical algorithm, based on fuzzy clustering and the framework of heuristic optimization. The aim of the cooperative surveillance task is to visit all the target regions with minimal time cost. Hence, an intuitive solution is to obtain paths of equal length for all UAVs. Rather than directly apply MTSP solver, we propose to first group the targets into several clusters based on the distances between them and the depots for each UAV. However, the resulting cluster, by using the distance-based hypothesis alone, may not always yield the correct solution — particularly, for the regions that are equally far from multiple depots. To deal with this problem, we reassign the targets near the boundary regions based on the following conditions:

$$\int_{\Omega} p(\boldsymbol{x} \in \Omega_i), \tag{1}$$

$$p(\boldsymbol{x} \in \Omega_i) = a_1 \exp^{-\left|\frac{\mathrm{num}(\Omega_i)}{\mathrm{AVRT}}\right|} + a_2 \frac{\mathrm{num}(\Omega_i)}{\mathrm{CA}(\Omega_i)}, \tag{2}$$

where $\mathrm{num}(\cdot)$ denotes the number of targets within the cluster Ω_i, AVRT represents the average number of targets for each cluster, and $\mathrm{CA}(\cdot)$ is the convex hull area for the cluster Ω_i. According to Eqs. (1) and (2), small and dense clusters are generally favored.

After clustering the targets to be visited based on the aforementioned scheme, the path-planning problem can thereafter be solved as a conventional TSP. If the speed of each UAV is assumed to be constant, the time-optimal solution is the same as the distance optimal for single TSP problem. Hence, the cost of the cooperative path-planning problem can be defined as follows:

$$\mathrm{cost} = \sum_{k=1}^{n} \mathrm{length}(\Omega_k), \tag{3}$$

where $\mathrm{length}(\Omega_k)$ denotes the length of the path for cluster k.

We apply a pigeon inspired optimization algorithm to obtain the optimal path [8], which has shown good performance in path-planning tasks. In the case where the depots are located at the middle of the map, the resulting path is more likely to have an even distribution of way points. If one of the depots is located in a corner behind another, the results can only satisfy its minimum length requirement. Hence, in this study, a combined cost function, by considering both the time and distance optimums, was used to determine the trajectory for each UAV. After determining the order of targets visited, the turning radius for each flight segment was determined by simply applying a Dubins path solver [9].

Simulation results. To verify the efficiency and accuracy of the proposed scheme, we compared the proposed method with GA and PSO-based algorithms to determine the surveillance path for a group of UAVs in a complex environment, which consists of a randomized distribution of 1000 targets with 4 UAVs taking-off from 4 different depots at [(−40,80); (40,120),(70,−20),(130,40)] km. The aforementioned methods were implemented using a standard PC (Intel i7 3.6 GHz and 16 GB memory) with MATLAB and C.

Fifty runs of simulations were performed to evaluate the performance of the proposed approach and other methods. Figure 1(a) depicts one of the resulting paths obtained by using the proposed work, and the convergence curves for the proposed method, GA-based and PSO-based solvers are illustrated in Figure 1(b). It can be observed from Figure 1(c) that the average run-time for the proposed method is rather short for the large-scale problem, i.e., this method is approximately 4.3 times faster than the GA and PSO-based MTSP solver, while 8.5% less accurate against GA and PSO. In terms of the stability of the resulting path, only slight variations were observed between runs, with the maximum spread of 3.5% between the best and worst solutions.

Conclusion. We proposed a two-step algorithm to deal with cooperative surveillance path-planning problems for a group of UAVs. In this study, a fuzzy clustering scheme was proposed, by considering the distance of targets to the depots, target density, and target amount for each cluster, which ensures that all the UAVs strive to obtain paths of equal length. In the second step of the algorithm, a heuristic optimization approach was applied to determine the optimal solution for each cluster. Simulations showed that the proposed algorithm achieves an extremely competitive run-speed and relatively high accuracy when compared with the conventional MTSP solver. It has the potential to be incorporate in board flight control and mission-planning systems.

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