A Local Optimization Technique for Assigning New Targets to the Planned Routes of Unmanned Aerial Vehicles

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***Abstract*— Using Unmanned Aerial Vehicles (UAVs) for reconnaissance purposes requires dynamic route planning. For example, when some of the UAVs are lost or new targets pops up during the mission, routes of each UAV should be re-arranged accordingly. This article proposes an iterative local optimization for the distribution of new targets to the existing routes in such circumstances. The proposed iterative insertion algorithm basically executes in phases. In the first phase of the algorithm, a selected UAV's route is updated by trying to insert new targets if possible. In the second phase, a 2-opt technique is applied to the modified UAV routes for minimizing the route distance. After the second phase, if there remains some uncovered targets we begin to run the first phase again. The proposed algorithm will terminate either all the new targets are covered or 2-opt technique does not produce any better route distances. The simulation results of the iterative insertion algorithm show the effectiveness and the success of the proposed algorithm.**

Index Terms— **UAV, dynamic route planning, target assignment, iterative insertion algorithm,**

I. Introduction

USING Unmanned Aerial Vehicles (UAVs) are one of the reconnaissance methods gaining popularity recently [1, 2, 3]. Since UAVs are very expensive and scare resources, UAV route planning is vital for increasing their effectiveness in monitoring targets [4]. Route planning can be static or dynamic [1, 5]. In static route planning, routes are constructed according to given UAVs and targets and do not change during the mission. However, in dynamic route planning, number of routes or UAVs can alter which requires the update of existing routes to adopt these changes. For example, some of the UAVs can be lost during the mission or new targets might pop up after the take-off.

In this work, we deal with dynamic route planning. We assume that we are given an initial list of targets and UAVs with a fixed flight range. Using Nearest Neighbor (NN) heuristic we create the initial route for each UAV. Then, new targets pop up and the routes are to be changed. One important consideration of the updating route can be the fact that we would not like to change the whole route, that is, create routes from scratch, due to several practical issues. Instead, we would like to update the existing routes by allocating new targets to the existing routes properly. Using this motivation we propose an iterative heuristic to update the existing routes with new targets. The proposed algorithm aims to cover maximum number of new targets as well.

Paper is organized as follows. In the following section we present the Iterative Insertion Algorithm (IIA) in details. The simulation model and the results of the experiments are summarized in Section 3. Then we concluded the work in Section 4.

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II. Iterative Insertion Algorithm

This article proposes an iterative local optimization for the distribution of new targets to the existing routes in dynamic route planning. In the proposed solution, it is supposed that all UAVs have the same flight ranges, their initial routes are planned, and they have already visited some of the targets according to these routes. Furthermore, for each UAV, the slack range which is the difference between the flight range and initial route distance is calculated.

Whenever some new targets appear, the proposed Iterative Insertion Algorithm executes as follows. In the first phase of the algorithm, an UAV with the highest slack value is picked and its route is modified by deleting a target whose deletion cause a maximum increase in the slack value. This target is appended to the end of the new target list. Then, we attempt to insert a new target to that UAV's route at a time. Adding a new target to an existing route causes an increase in the route distance, which is called update cost. If the update cost is not greater than the slack range, the new target is inserted to the route. After testing the insertion of the new target to any location in the existing route, we select the location which cause minimum update cost. The target is inserted to this location in the route list.

After finishing attempts with all new targets, if any of them is left over, insertion process is executed with the UAV having the next highest slack range as described above until either all UAVs or new targets are finished. If there are still uncovered new targets after trying all UAVs, the algorithm proceeds the second phase in which a 2-opt technique is applied to the modified UAV routes for increasing the slack ranges. Then, the first phase of the algorithm is re-run for the remaining uncovered targets. Algorithm will terminate either all the targets are covered or the 2-opt technique does not produce any better slack value.

III. Simulation Model And Experiment Results

The proposed algorithm is implemented using Mason simulation library [7] and tested with various experiments for different parameter settings and TSP data files [6]. The preliminary results show the effectiveness and the success of the proposed iterative insertion algorithm.

A. Simulation Model

We assume that targets locations are given in the selected TSP file. We first randomly select a base location among these targets so that all UAVs are located on this location. Then according to the specified initial target number (ITN), target locations are chosen and the initial routes for all UAVs to cover these targets are generated using Nearest Neighbor (NN) heuristic. Then, the rest of the TSP file is used as the new target list.

To cover the new targets, we apply the proposed iterative insertion algorithm (IIA). To evaluate the result of the proposed heuristic, we also run NN heuristic to create new UAV routes for all the targets.

For each set of experiments we run the simulation 40 times and get the averages of the observed results.

As a performance metric, we select to count the number of targets in the routes created by any algorithm. First, for the given Initial Target Number (ITN) we randomly select targets as the initial targets. We create the first routing using the NN heuristic. The number of targets in this routing is called TN_{INN}. We assume that new targets pop up as the number of Pop-Up Target Number (PTN). For covering these new targets we first apply the NN heuristic from scratch. The recalculated routing plan consists of TNRNN number of targets. Then as a last step, we apply the proposed Iterative Insertion Algorithm (IIA) on the initial routing and create a new routing plan which has TNIIA number of targets. The success of the IIA is defined as in Eq. (1).

$$\text{Success} = \frac{\text{TN}_{\text{IIA}} - \text{TN}_{\text{RNN}}}{\text{TN}_{\text{RNN}}} * 100 \tag{1}$$

B. Experiment Results

In these experiments, we use CH130.tsp file that has 130 coordinates which are used for the target and base locations. TABLE I summarizes the target numbers that are covered by the planned routes when 2 UAVs are employed with a fixed Flight Range 1500 meters. The IIA successfully plans more targets to be visited by the UAVs for different initial target numbers compared to the NN heuristic. For example, when 40 new targets are pop up IHH can route about 57 targets while NN can route about 53 targets on the average. In this table we observe that as the new target number gets less, the success decreases as well. This is probably due to the fact that there is less room to optimize the solution since we have fewer new targets to insert into the existed initial NN routes.

TABLE I
Number of targets covered by the heuristics when 2 UAVs with Flight Range = 1500 are used

ITN	PTN	#UAV	TN_{RNN}	TN_{IIA}	Success (%)
70	*60*	*2*	*52.90*	*58.47*	*11*
90	*40*	*2*	*52.70*	*56.89*	*08*
110	*20*	*2*	*53.37*	*57.32*	*07*

As a second experiment, we change the number of UAVs. In TABLE II, we observe that the IIA generates better results for different number of UAVs. However, as the number of UAVs is increased the success ratio is decreased.

TABLE III
Number of targets covered by the heuristics when different number of UAVs with Flight Range = 1500 are used

ITN	PTN	#UAV	TN_{RNN}	TN_{IIA}	Success (%)
70	*60*	*2*	*52.90*	*58.47*	*11*
90	*60*	*4*	*72.68*	*79.15*	*09*
110	*60*	*4*	*89.87*	*94.74*	*05*

To observe the change in the initial routing while covering the new targets we provided the figures below. As discussed above, we can opt for a least difference in the existing UAV routes while appending new targets. In the figures the base is marked with a square, and targets as circles. In Fig. 1, we see the initial NN route created for the initial targets and new targets. Fig. 2 shows the routing of recalculated NN heuristic and the updated initial NN routing by the proposed IIA. As seen in the figures, the proposed IIA causes fewer changes in the existing initial UAV routings compared to the result of the recalculated route. Thus, we can argue that the proposed heuristics can generate new routings for the UAVs with more targets covered and with fewer changes occur in the existing routes. For this specific example, TN_{INN} is 44, TN_{RNN} is 52, and TN_{IIA} is 59.

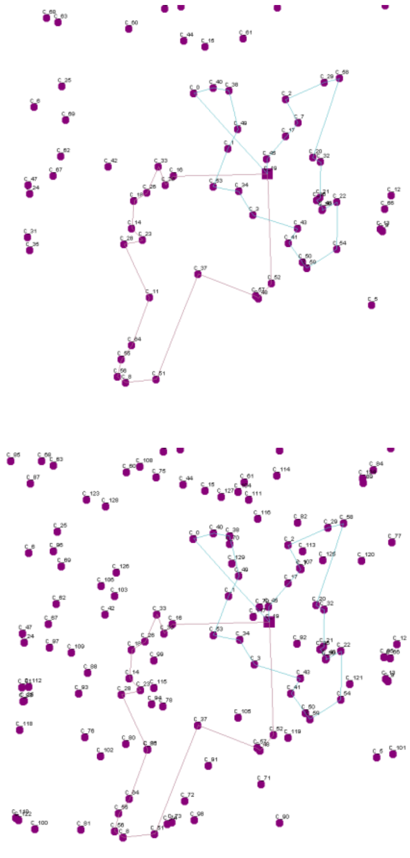

Fig. 1. (on the top) the initial NN route for the initial targets and (on the bottom) the pop-up targets

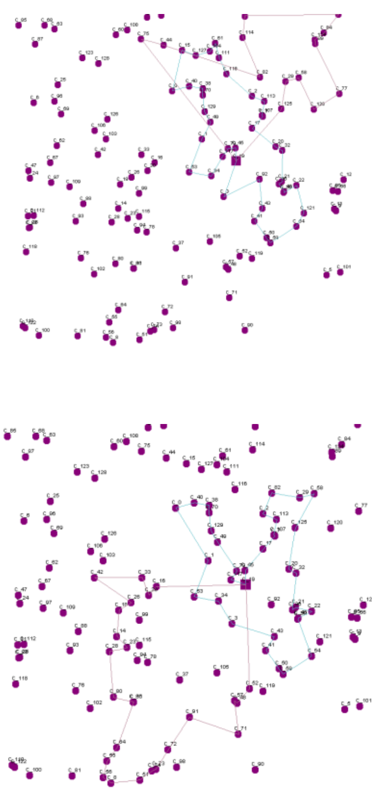

Fig. 2. (on the top) the recalculated NN route for the new targets whereas (on the bottom) the route created by the proposed IIA

IV. CONCLUSION

In this work, we attack the problem of dynamic route planning by designing an iterative insertion algorithm. We compare the results of the initial experiments and have observed encouraging advantage of the proposed heuristic over the NN heuristic. As a future work, we aim to extend our work by introducing more comprehensive performance metrics and conducting the experiments with different TSP files.

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BIOGRAPHIES

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