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OPTIMAL PATH PLANNING FOR A TEAM OF HETEROGENEOUS DRONES TO MONITOR AGRICULTURAL FIELDS

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ABSTRACT

In this work, we investigate the problem of finding the minimum coverage time of an agricultural field using a team of heterogeneous unmanned aerial vehicles (UAVs). The aerial robotic system is assumed to be heterogeneous in terms of the equipped cameras' field of view, flight speed, and battery capacity. The coverage problem is formulated as a vehicle routing problem (VRP) [1] with two significant extensions. First, the field is converted into a graph, including nodes and edges generated based on sweep direction and the minimum length of UAVs' footprints. Second, the underlying optimization problem accounts for aerial vehicles having different sensor footprints. A series of simulation experiments are carried out to demonstrate that the proposed strategy can yield a satisfactory monitoring performance and offer promise to be used in practice.

Keywords: Heterogeneity; Vehicle routing problem; Remote sensing; Unmanned aerial vehicles (UAVs).

1 Introduction

With the advancements in technology, there has been much ongoing research work on the use of robots for precision agriculture applications to improve the quality and quantity of crop production [2]. Candiago *et al.* in [3] deployed a multi-rotor aerial vehicle to monitor a vineyard and a tomato farm, where the col-

lected image data were then analyzed and evaluated. Berni *et al.* developed an autonomous aerial system to remotely monitor a vegetation field with thermal and imaging sensors in [4]. Bakker *et al.* in [5] suggested an autonomous navigation ground robot to map crop rows and monitor sugar beets in a field.

Due to the limitations of a single unmanned vehicle, multiple robots have been used to reduce the time taken to accomplish tasks and improve overall system performance [6]. In [7], a system consisting of aerial and ground vehicles was used to monitor and control pests and weeds in three different agricultural fields. Authors in [8] deployed a multi-robot system consisting of an unmanned ground vehicle (UGV) and an unmanned aerial vehicle (UAV) to monitor crops in a farm and collect crop data. Besides, the use of remote sensing with a team of aerial robots has recently received considerable attention for various purposes like collecting visual data of crops and fields and the map reconstruction of the fields. For instance, Chao *et al.* [9] proposed multiple automated aerial vehicles to remotely detect water level of crops based on image analysis. Moreover, in [10], a team of UAVs was proposed to monitor and control the presence of pests in a farm.

In practical scenarios, teams of heterogeneous UAV systems might be deployed that have different capabilities (e.g., dynamics, fields of view, speeds, or battery charges among others). The field of view is an important factor that should be considered when solving coverage optimization problems for UAVs. Ahmadzadeh *et al.* in [11] proposed a coverage method using four heterogeneous UAVs with different footprints on the ground.

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Each camera's field of view was defined to depend on the heading, back angle, and position of the vehicle and was considered in solving the coverage problem. In [12], the authors also deployed an algorithm for a team of heterogeneous UAVs with different circular fields of view.

For optimal deployment of a team of heterogeneous UAVs, the coverage areas can be modeled as a graph so that each of the vehicles can visit the edges of the graph at least once and avoid overlapping [1]. In [13], Faryadi *et al.* proposed an area coverage method by converting the field of study into a corresponding weighted graph with different nodes and edges to simplify path planning. Davoodi *et al.* in [14] modeled a target agricultural field by a weighted undirected graph with nodes defined around plant rows. Although drones have no limit to flying in any direction, to avoid sharp turning and to move constantly during their missions, they are forced to monitor the area executing back and forth motions in most studies. Huang *et al.* in [15] modeled a coverage area as a directed graph to determine the optimal coverage direction by visiting each region of the area in a back-and-forth motion. Similarly, in deploying multiple robots to spray insecticides on a farm in a back-and-forth movement, Luo *et al.* [16] modeled the field by a rectangular directed graph so that the flight trajectories of the robots are parallel to the edges of the field. After converting the area into a graph consisting of nodes and edges, the coverage problem is formulated as a vehicle routing problem (VRP), and each node is considered as a customer that must be visited with a single vehicle (drone). In [17], a solution to the VRP problem for multi-UAVs was proposed by defining the objective function based on the information collected by the vehicles' cameras. In [18], Guerriero *et al.* addressed a dynamic VRP in which the nodes of the graph represent the temporal and spatial coverage points.

In this work, our main objective is to solve the problem of minimizing the coverage time of monitoring an agricultural field using a team of heterogeneous UAVs. More specifically, we assume that UAVs can have different fields of view, battery charges, and speeds. Our work is motivated by the methodology used in [19], in which a fleet of UAVs was deployed to complete a mission of field coverage. In [19], the coverage area was modeled by a directed graph, and the optimization problem was defined as a min-max problem such that the time spent traveling through the longest route (that is maximum flight time) is minimized. The setup time for prepping and launching the vehicles was also considered. However, in this paper, we specify the number of UAVs and consider the field of view of the vehicles' cameras in the formulated optimization problem.

The remaining sections of this paper are organized as follows: Section 2 provides a detailed description of the problem we study here, as well as our proposed methodology to address that. Section 3 presents the simulation results, and Section 4 concludes the paper and provides perspectives for future work.

2 Problem Formulation and Proposed Solution Method

The main goal of this work is to find a solution to the optimal deployment problem of M heterogeneous UAVs (drones) in an agricultural field represented as a weighted graph in such a way that the maximum traveling time by them be minimized. We assume that a team of autonomous drones equipped with RGB cameras with different fields of view needs to be deployed to monitor the field and to collect data from plant rows. Assuming that cameras are parallel to the ground, L_m is used to denote the camera's footprint on the plane for m -th drone. Moreover, deployed drones are assumed to be different in terms of the maximum flight time t_m and flight speed V^m , where $m \in \{1, 2, \dots, M\}$, and each drone flies at a fixed height H_m which is chosen in such a way that the camera can take sufficiently high-resolution images.

The deployment problem will be solved following the steps below: (i) the given field is modeled as a weighted graph by considering the parallel coverage rows with optimum distance [15]; (ii) the coverage rows are partitioned/divided between different drones by formulating and solving a mixed-integer linear programming (MILP) optimization problem; (iii) based on the result of solving MILP, optimal trajectories for drones are generated so that they can effectively monitor the whole field.

2.1 Sweep direction and coverage rows

In most coverage applications, coverage time and energy are two main factors contributing to the cost-efficiency. Consequently, the coverage path must be generated so that a combination of total time and energy is minimized. To this end, similar to the method proposed in [15], the area is decomposed into subregions based on a specific sweep direction, and all drones must fly over these regions using back and forth motion along the coverage rows, which are perpendicular to the sweep direction. For agricultural applications, the main purpose of deploying drones over the field is to monitor plant rows and capture appropriate images. To achieve this goal, the best sweep direction for drones is defined in such a way that they can fly along the plant rows, as shown in Fig. 1.

After defining the sweep direction, coverage rows will be arranged with a fixed distance, which is calculated as a function of the smallest footprint of the on-board cameras on the ground. First, as shown in Fig. 2, the width L_m representing the camera's footprint for the m -th drone is calculated as [19]

$$L_m = H_m \frac{l_m}{f_m}, \quad (1)$$

where l_m is the width of the camera, and f_m denotes the focal length of the cameras' lens for the m -th drone.

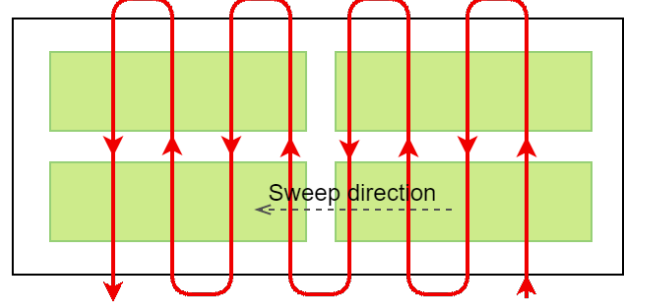
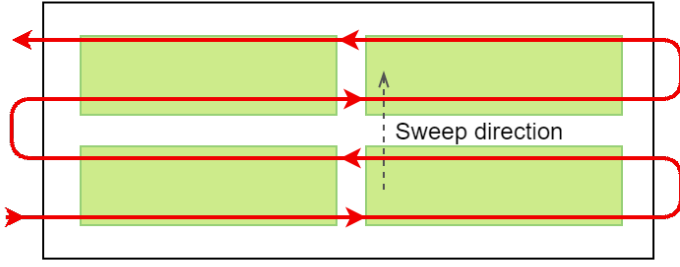


FIGURE 1: Left: sweep direction perpendicular to the plant rows; Right: sweep direction along the plant rows.

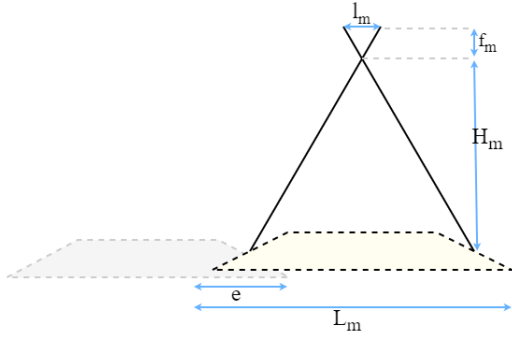


FIGURE 2: Illustrative example showing the field of view.

For M heterogeneous drones with different footprints, L is chosen as

$$L = \min\{L_1, L_2, \dots, L_M\}. \quad (2)$$

Then, the number of coverage rows is

$$N_l = \left\lceil \frac{w}{L(1-e)} \right\rceil, \quad (3)$$

where w represents the field's width and $e \in (0, 1)$ is the fraction showing two images' overlap. Hence, the distance between two rows is

$$l = \frac{w}{N_l}. \quad (4)$$

Similar to our previous work [13, 20], the field is converted into a weighted graph represented by $G = (V, E, C)$ with the node set $V \in \{1, 2, \dots, N\}$ shown in Fig. 3. Also, $E \subseteq |V| \times |V|$ is a set

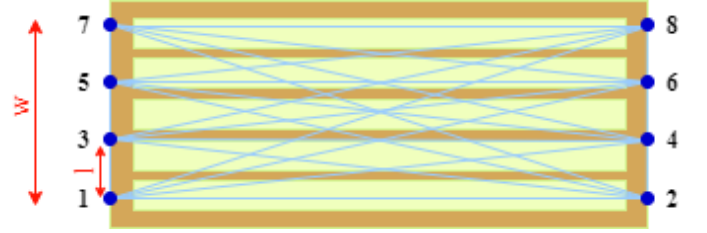


FIGURE 3: Field modeling as a graph.

of arcs (edges), and C is the specific costs (metric lengths) of the edges. In this work, c_{ij} represents the Euclidean distance between nodes i and j . The novelty of this method is in arranging coverage rows with the specific distance calculated based on the minimum length of camera's footprints (2) between the drones' on-board cameras.

2.2 Coverage rows partitioning

To divide the coverage rows between the vehicles considering their sensing differences, we define a new parameter ρ_m representing the ratio of m -th drone's footprint to the minimum length L as

$$\rho_m = \left\lceil \frac{L_m}{L} \right\rceil. \quad (5)$$

As shown in Fig. 4, ρ_m is defined to calculate the number of rows that can be covered (monitored) by m -th drone while it is flying over one coverage row.

After generating the field graph G , inspired by the method proposed in [19], the coverage problem is transformed into a vehicle routing problem (VRP) with specific constraints. It should be noted that our work extends the results of [19] with two specific contributions that make our proposed problem unique. First, unlike [19], our optimization problem (VRP) is formulated as a function of the drones' footprints and then solved for vehicles with different sensing capabilities; second, unlike most routing

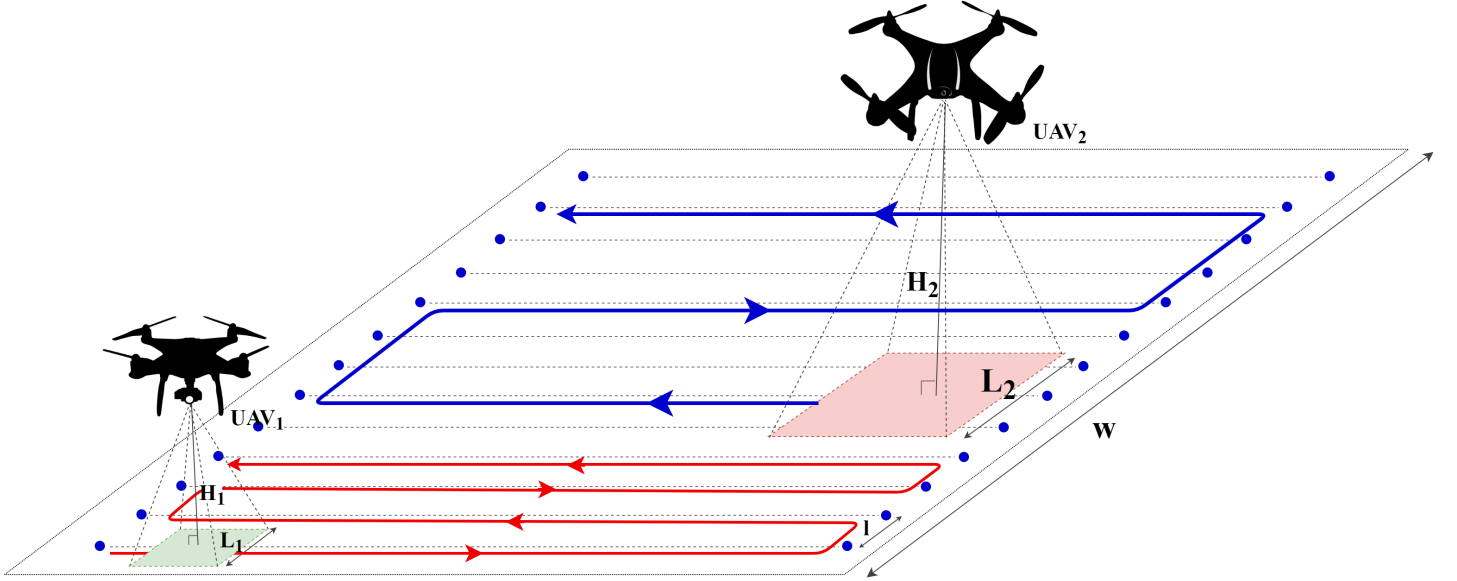


FIGURE 4: Illustrative example showing different footprints of two heterogeneous drones.

problems, in our work, solving the VRP problem results in partitioning coverage rows between vehicles and then optimum routes are generated based on cameras' footprints.

To formulate this optimization problem as a VRP, each node of the field graph is considered as a customer that needs to be visited by one drone. Moreover, decision variable $E_{ij}^m \in \{0, 1\}$ is defined indicating if $\text{arc}(i, j)$ is used on the route or not by m -th vehicle. Like most vehicle routing problems, in this application, the main objective is to partition nodes between all drones in order to minimize the time of mission. By knowing the m -th drone's flight speed V^m and cost matrix C , the flight time of m -th drone is calculated as follows

$$t_m = \sum_{i=0}^N \sum_{j=0}^N \frac{c_{ij}}{\rho_m V^m} E_{ij}^m, \quad (6)$$

where c_{ij} denotes the entry (i, j) of the cost matrix C , and index 0 refers to the *depot* node. Then, the longest traveling time between all drones is

$$T_{max} = \max(t_m). \quad (7)$$

With the purpose of minimizing the longest traveling time taken to cover the entire area, our optimization problem is

$$\min(T_{max}), \quad (8)$$

subject to several constraints explained below and given in equations (9) - (17).

The following constraint is imposed to ensure that the m -th drone's total coverage time does not exceed the maximum time

$$\sum_{i=0}^N \sum_{j=0}^N \frac{c_{ij}}{\rho_m V^m} E_{ij}^m \leq T_{max}. \quad (9)$$

For limiting the longest flight route of each drone with its battery capacity, another constraint is imposed as follows

$$\sum_{i=1}^N \sum_{j=1}^N \frac{c_{ij}}{\rho_m V^m} E_{ij}^m \leq \tau_m, \quad (10)$$

where τ_m denotes the maximum battery time duration of m -th drone.

Constraint (11) below enforces each vehicle to leave the depot (node 0) and arrive at a determined customer

$$\sum_{i=1}^N E_{0i}^m = 1. \quad (11)$$

Moreover, (12) guarantees that all drones would return back to the depot:

$$\sum_{j=1}^N E_{j0}^m = 1. \quad (12)$$

Constraint (13) ensures that each $arc(i, j)$ is monitored only once

$$\sum_{m=1}^M \sum_{i=1}^N E_{ij}^m = 1, \quad i, j \in \{1, 2, \dots, N\}, \quad i \neq j. \quad (13)$$

The following constraint limits drones' entrance and exit flows to guarantee that the same vehicle would visit and leave each node of the graph

$$\sum_{i=0}^N E_{ip}^m - \sum_{j=0}^N E_{pj}^m = 0, \quad p = 0, 1, 2, \dots, N. \quad (14)$$

In addition, equation (15) enforces drones to fly over coverage rows perpendicular to the given sweep direction and along the plant rows

$$\sum_{m=1}^M E_{i,i+1}^m + \sum_{m=1}^M E_{i+1,i}^m = 1, \quad i = 1, 2, 3, \dots, N. \quad (15)$$

Two important constraints (16) and (17) are defined to impose drones executing back and forth motions to cover the area [19]:

$$\sum_{m=1}^M E_{i,i+1}^m - \sum_{m=1}^M \sum_{(j=0,2,4,\dots,ni+1)}^N E_{(i+1,j)}^m = 0, \quad i = 1, 3, \dots \quad (16)$$

$$\sum_{m=1}^M E_{i,i-1}^m - \sum_{m=1}^M \sum_{(j=1,3,5,\dots,ni-1)}^N E_{(i-1,j)}^m = 0, \quad i = 2, 4, 6, \dots \quad (17)$$

And finally, constraint (18) given below guarantees that the VRP solution would make drones avoiding sub-tours:

$$y_i - y_j + N \sum_{m=1}^M E_{ij}^m \leq N - 1, \quad i, j \in \{1, 2, 3, \dots, N\}, \quad i \neq j, \quad (18)$$

where $y_i, y_j \in \{0, 1\}$ are additional binary variables.

After solving the optimization problem, represented as a VRP, all nodes of the field graph and the corresponding coverage rows are divided among a team of heterogeneous drones considering their footprint ratios, flight speeds and battery limitations (see Fig. 4). As an example, Fig. 5 shows coverage regions resulted from solving the VRP for two drones with different footprints. In this figure, the edges plotted with solid red lines from node 1 to node 8 are assigned to the drone with $\rho = 1$

and dashed blue edges from node 9 to 26 are assigned to the drone with $\rho = 2$.

In the ensuing subsection, a path planning method will be applied to generate the optimal flight route for each drone with the purpose of monitoring its partition resulted from the VRP solution.

2.3 Drones' path planning

By solving the afore discussed MILP optimization problem, the field graph G is partitioned into m sub-graphs, each of which is assigned to one of the drones. Then, the optimal trajectories for each drone should be generated to make it capable of flying over these rows and collect image data of the corresponding sub-region. To generate optimal trajectories for UAVs to cover the area modeled as a weighted graph, coverage rows are divided between agents to minimize the total time of the mission. Then, an optimal trajectory is needed to enforce UAVs to fly over these rows and collect image data.

As explained before, the camera's footprint ratio denoted by ρ_m represents the number of coverage rows monitored by the m -th drone while flying over only one row. For instance, in Fig. 5, the green squares show camera's footprint of the first drone with $\rho_1 = 1$ while the red ones (larger ones) represent the second drone's footprint with $\rho_2 = 2$. From Fig. 5, it is clear that when a drone is flying over an arbitrary edge (i, j) , in addition to this edge, it will simultaneously cover R_m neighboring rows ($R_m/2$ rows from the right and left sides of the (i, j) -th one), where

$$R_m = 2(\rho_m - 1). \quad (19)$$

For instance, in this figure, dashed blue trajectory shows the VRP solution for the drone with $\rho = 2$ and it is in the following order: $depot \rightarrow 9 \rightarrow 10 \rightarrow 12 \rightarrow 11 \rightarrow 13 \rightarrow 14 \rightarrow 16 \rightarrow 15 \rightarrow 17 \rightarrow 18 \rightarrow 20 \rightarrow 19 \rightarrow 21 \rightarrow 22 \rightarrow 24 \rightarrow 23 \rightarrow 25 \rightarrow 26 \rightarrow depot$.

However, this trajectory is not optimal and using R_m as in (19), after completing each row, $2R_m$ nodes should be skipped to find the next best node and finally the following optimal route is obtained

$depot \rightarrow 12 \rightarrow 11 \rightarrow 17 \rightarrow 18 \rightarrow 24 \rightarrow 23 \rightarrow depot$.

Based on the above explanation, when the second drone (with $\rho_2 = 2$) flies over an arbitrary row, in addition to that row, it also monitors $2(2 - 1) = 2$ more (left and right) neighboring rows. Therefore, after solving the proposed MILP optimization problem that partitions the field graph between different drones, the optimal trajectories for all the drones will be generated following the approach described above.

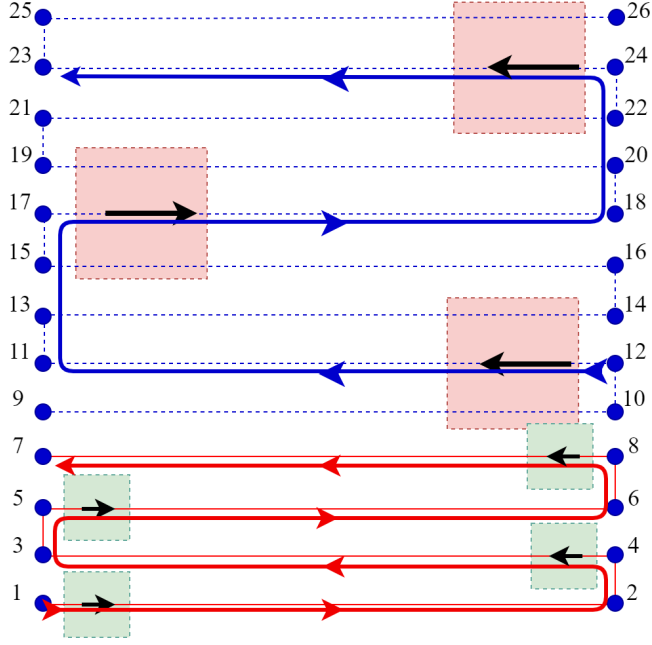


FIGURE 5: Illustrative example showing path planning for two drones with different fields of view.

3 Simulation Results

In this section, a series of simulation results is provided to demonstrate the proposed methods and validate their effectiveness. Our proposed optimization problem was implemented in Python using MIP package to solve the underlying mixed-integer linear program. In this setup, we assumed that there is a $20 \times 50 \text{ m}^2$ agricultural field, including 32 plant rows. It is worth mentioning that the number of coverage rows is independent of the number of plant rows and is computed based on the width of the field and the minimum footprint of the drones' cameras. Two drones are deployed from node 0 (defined as a depot), and their mission is to fly cooperatively over the field and collect image data. First, to convert the field into a weighted graph, we defined $L = 2 \text{ m}$ as the minimum of the cameras' footprint and then based on equations (3) and (4), the field with a width of 50 m is divided into 25 rows arranged from node 1 to node 50, as presented in Fig. 6. Our proposed results are applied to the following three different scenarios.

In the *first scenario*, we consider two homogeneous drones. Indeed, it is assumed that they are equipped with cameras with the same properties, their batteries are fully charged (at the beginning of the mission), and they both fly at the same speed. In this case, $\rho_1 = \rho_2 = 2 \text{ m}$ and, as shown in Fig. 6, by solving the VRP for this setup, flight trajectories are generated for two drones with the same characteristics leading to the field being equally divided between the two drones to cover.

In the *second scenario*, it is assumed that the second drone

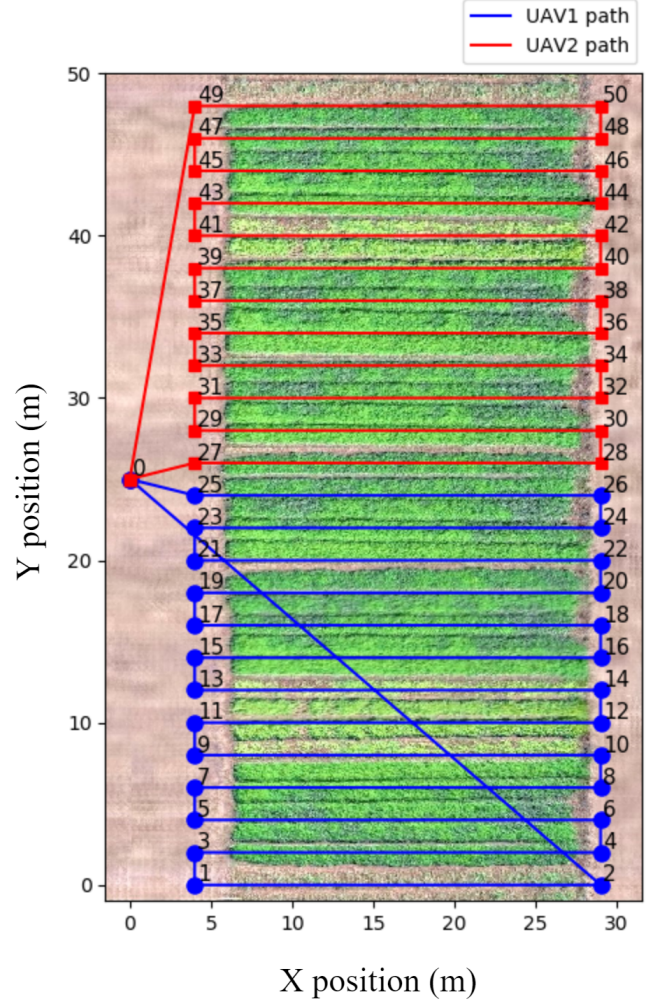


FIGURE 6: Simulation result showing the path planning outcome for two homogeneous drones.

has smaller camera's footprint than the first one ($L_1 = 2L_2 = 4 \text{ m}$), but its battery time duration is two times larger than the first drone ($\tau_1 = \frac{1}{2}\tau_2 = 1500 \text{ s}$). When the first drone flies from node 8 to 7, considering its footprint ratio ($\rho_1 = 2$), it can monitor arcs (5,6) and (9,10) simultaneously. Fig. 7 shows flight trajectories for each drone based on the number of rows that they can monitor flying over each edge. As observed, the first drone is allocated and covers almost twice the field rows more than the second drone.

In the *third scenario*, we assumed that the first drone that has a larger field of view is fully charged, and its battery time duration is equal to the second drone. Fig. 8 indicates the flight routes for this scenario. As it is clear from this figure, most of the rows are assigned to the first drone because of its large footprint ratio.

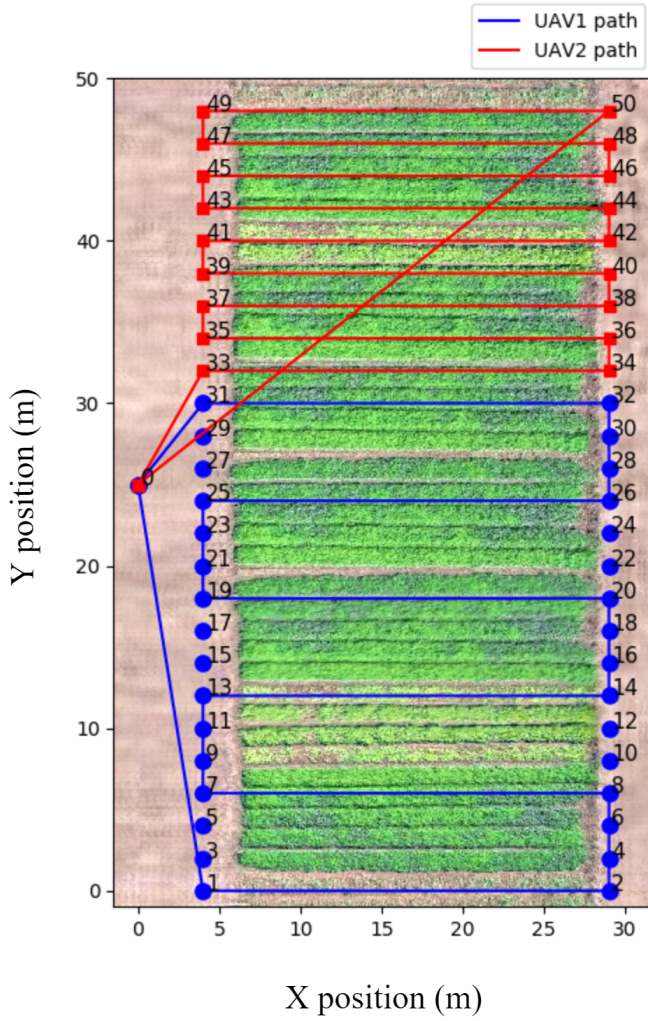


FIGURE 7: Simulation result demonstrating the path planning for two drones with different fields of view. First drone's footprint is assumed to be twice of that of the second drone, but its battery charge is half of the full state.

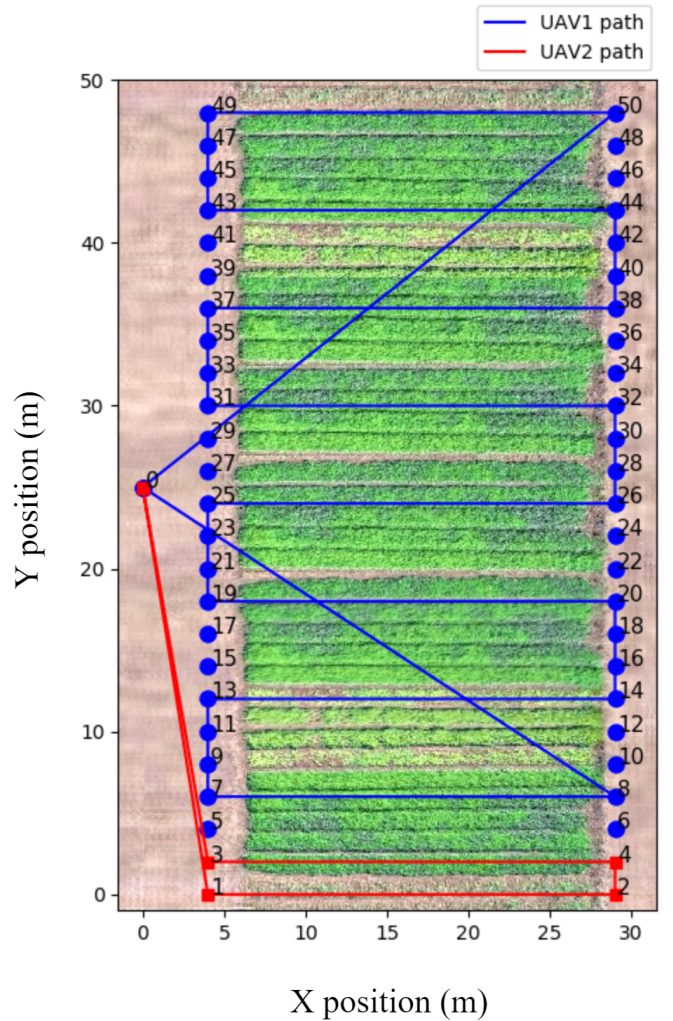


FIGURE 8: Simulation result showing the path planning outcome for two drones with different fields of view, where the first drone's footprint is twice the second drone's but their battery charge is the same (both fully charged).

4 Conclusion and Future Work

In this paper, we formulated (and solved) the problem of optimal deployment of a team of heterogeneous drones in an agricultural field in such a way to minimize the coverage time. We considered a team of drones with different cameras' field of view, flight speeds, and batteries' remaining charge. The field was first modeled as a graph with a set of nodes arranged considering the minimum of footprints. The underlying optimization problem was converted to a vehicle routing problem subject to a set of specific constraints enforcing vehicles to travel along the plant rows in a back and forth motion. The optimization problem was formulated as a mixed-integer linear program (MILP), and

the performance of the proposed VRP solution was validated using various simulation studies to find the optimal flight path in a given agricultural field.

The authors are currently investigating a new approach to address the case with different flight heights for a team of drones, with the goal of finding the optimum cameras' footprint as a function of the height at which drones fly. The experimental validation (field study) of the proposed method is also underway.

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