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Aerial Robot Coverage Path Planning approach with Concave Obstacles in Precision Agriculture

The Hung Pham¹ and Yasmina Bestaoui² and Said Mammam³

Abstract—In this paper, we present a new approach for maximizing the coverage path planning while minimizing the path length of an aerial robot in agriculture environment with concave obstacles. For resolving this problem, we propose a new cellular decomposition which is based on a generalization of the Boustrophedon variant, using Morse functions, with an extension of the representation of the critical points. This extension leads to a decrease of the number of cells after decomposition. The results show that this new cellular decomposition works well even with several concave obstacles inside the environment. Furthermore, for path planning, the cells are divided again into two classes, leading to have a cell set better suited for use of the traveling salesman problem (TSP) to get complete coverage. Genetic Algorithm (GA) and TSP algorithm are applied to obtain the shortest path. Then, an approach is also proposed to maximize the scanned area on the working area with obstacles. The proposed method can be applied in precision agriculture for monitoring insects and other crop pests. The effectiveness of the proposed method has been verified on Matlab/Simulink.

I. INTRODUCTION

Coverage path planning (CPP) is one of the most important tasks for robot motion and missions. CPP is the determination of a path that a robot must take in order to pass over each point in an environment while avoiding obstacles. Based on the path that has been generated, robots can accomplish their predefined tasks such as cleaning, painting, window cleaning, and inspection of complex structures. It will be easier if there is no obstacles on the working area, however obstacles are always present. In order to create way-points for the robot, first, the environment needs to be divided into smaller parts called cells. These cells are obstacles-free and the robot can freely move inside them. CPP has been extensively studied in recent years for applications such as vacuum cleaning robots [1], painter robots [2], path planning for autonomous underwater vehicles [3], demining robots [4], lawn mowers [5].

Although the land resource on the Earth is limited, the human population is growing very fast on the globe. Thus, human being is now facing a very serious challenge of sustainable food and energy production. In that sense it is expected that field crop production is going to be more intensified, but with minimum unfavourable effect on environment. For improving the food production which can satisfy human needs, it is necessary to monitor the state of the crop such as the health and the pest of the plants. Several

types of agricultural robots have been widely used to get the information of the crop as mobile robot, unmanned aerial vehicle (UAV), or the collaboration of both of them. Because of their high mobility and low cost, UAVs are now more and more expanding to commercial, scientific, recreational, and other applications, such as security and surveillance, product deliveries, aerial photography, especially in agriculture. Examples of applications of UAVs in agricultural studies are becoming more noticeable in the literature. In [6], Hunt et al. evaluated an aerobatic model aircraft for acquiring high-resolution digital photography to be used in estimating the nutrient status of corn and crop biomass of corn, alfalfa, and soybeans. In [7], Ahmed et al proposed a path planning which optimizes the turning curve of the UAV trajectory to reduce the distance as well as the cost but coverage was not considered.

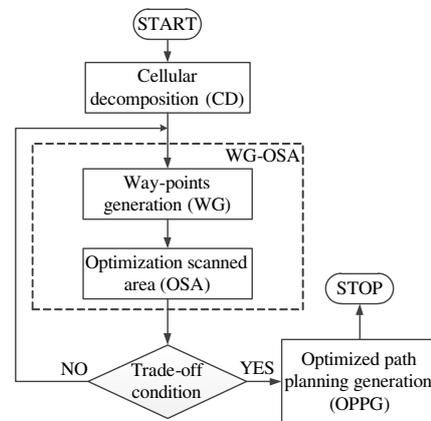


Fig. 1: Proposed algorithm

The contribution of this paper focuses on maximizing the coverage path planning and minimizing the path length of an aerial robot in agriculture environment with concave obstacles. The algorithm is depicted in Fig. 1. It is a combination of distance minimization and profit maximization. For accomplishing this problem, one has to resolve three main tasks. The first task is dedicated for cellular decomposition(CD) (Fig. 1). A new cellular decomposition is based on a generalization of the Boustrophedon variant [8], using Morse functions [9], with an extension of the representation of the critical points. The feature of this extension is that the number of cells after decomposition is decreased compared to the decomposition methods in [8], [9]. With this new proposed approach, the environment can be divided into a number of separating obstacles and

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obstacle-free regions. In each obstacle-free region which can be called obstacle-free cell, the aerial robot can make back and forth motion to cover the whole working area. Based on the cells that have been decomposed by CD, the second task is aiming to generate way-points in each cell (WG in Fig. 1) and maximize the percentage of coverage (OSA in Fig. 1). The trade-off condition between percentage of coverage and number of way-points is the condition for ending the algorithm. Finally, in the third task, once the cells have been created by CD, the way-points have been created by WG and OSA, the cells are divided again into two classes, leading to have a cell set better suited for using the TSP algorithm to get complete coverage. GA and TSP algorithms with some modifications are applied to obtain the shortest path for the aerial robot to make complete coverage.

The remainder of this paper is organized as follows. In section II, the system model used will be introduced. The approach and algorithm for the new cellular decomposition method are given in section III. Then, the use of genetic algorithm and travelling salesman problem with some additional constraints for minimizing the path length when moving between cells, optimization process of the percentage of coverage, and the trade-off between the percentage and the number of way-points will also be presented in this section. Section IV is dedicated for conclusion and future work.

II. SYSTEM MODEL

A. UAV platform

This paper considers a quad-rotor equipped with a video camera mounted on a gimbal stabilizer, which compensates for small rotation displacements that may be experienced by the UAV during navigation. The objective of the mission is to take images of the whole area of plants by a dedicated spectral camera. Based on spectrum study of images that have been taken, one can have the information about the health and pest of the plant.

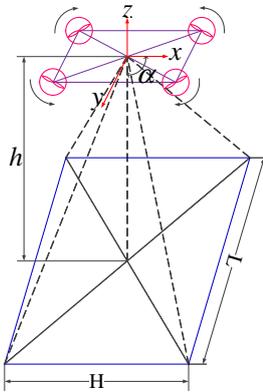


Fig. 2: UAV with frame picture capture

We assume that images are taken by special spectral camera which has the following parameters :

- Image frame is rectangle with the length and width are respectively L and H .

- Images have to be taken such that they have the same direction and the overlap regions on the horizontal and vertical sides as dL and dH (in Fig. 3)

For the optimization problem, there is one constraint that all the center of the rectangles are in the obstacle-free region.

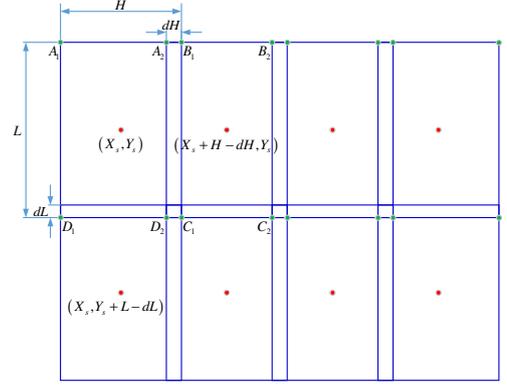


Fig. 3: Picture frames

Without loss of generality, we consider that the working area is a rectangle. If the area is not a rectangle, it is possible to embed it into a rectangle area by adding more obstacles to the original area.

B. Add the geometry of the quad-rotor to each obstacle

In the process of performing its tasks, the UAV has to avoid the obstacles. Therefore, if we consider this UAV as a circle of radius r (in Fig. 4a), the distances from all the border points of obstacles to the center of UAV circle have to be greater or equal to r . For simplicity to consider the UAV as a point, it is necessary to augment the size of the obstacles by a radius dependent on the geometry of the drone and its footprint. At each border point of the obstacle, the operator draws a circle with radius r and considers the new obstacle is inside the red lines (in Fig. 4b).

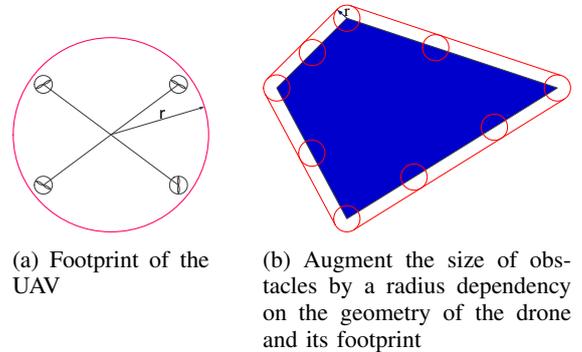


Fig. 4: UAV footprint and augmentation of the size of obstacles

III. NEW APPROACH FOR COVERAGE PATH PLANNING

A. Cellular decomposition (CD in Fig. 1)

Several cellular decomposition methods have been studied as trapezoidal decomposition technique [10], boustrophedon

decomposition [8], and Morse-based cellular decomposition [9].

In the trapezoidal decomposition technique [10], the free spaces are divided into trapezoidal cells. There are two parallel sides on each cell, and each cell can be covered by simple back and forth motion parallel to either side. Therefore, the whole working area can be totally scanned by visiting each cell in the adjacency graph. A vertical line is swept from left to right through the working area of the robot. Each time the line encounters a vertex of a polygon, one can say that an event occurs. Three types of events are defined : IN, OUT, and MIDDLE. In an IN event, the current cell is closed and two new cells are opened. When an OUT event occurs, the current two cells are closed and a new cell is created. Finally, MIDDLE event is the event that a current cell is closed and a new single cell is initiated. Consequently, by using these three events, the environment can be totally divided into separated trapezoidal cells.

A drawback of the trapezoidal decomposition is that it generates many cells that, intuitively, can be merged together to form bigger cells. This is clearly an inconvenient, as the more cells are present, the longer the final coverage path is. This happens because the trapezoidal decomposition creates only convex cells. However, non-convex cells can also be completely covered by simple motions. To overcome this limitation, the boustrophedon cellular decomposition was proposed. The boustrophedon decomposition is similar to the trapezoidal decomposition introduced above, but it only considers vertices where a vertical segment can be extended both above and below the vertex. The vertices where this occurs are called critical points.

The boustrophedon decomposition [8] addresses the issue of redundant movements by merging together cells between successive IN and OUT movements. The major difference is in the case of a MIDDLE event, where no new cell is formed, but the current cell is updated in width. So cells are only created on change of connectivity, as a result the number of cells are less than in the case of trapezoidal decomposition. The point which changes the connectivity of the cell is termed as a critical point. In the implementation of this algorithm, the MIDDLE event is replaced by two new events called – FLOOR and CEILING. The FLOOR event corresponds to vertices on top of obstacles, while CEILING event corresponds to vertices that are at the bottom of obstacles. Both an IN event as well as an OUT event are associated with FLOOR and CEILING pointers. So for a given cell, CEILING and FLOOR pointers points to the top and bottom of a cell.

In [9], Acar et al generalized the boustrophedon decomposition by proposing a cellular decomposition approach based on critical points of Morse functions. In this paper, the authors show that the boustrophedon decomposition is a particular case of Morse decomposition. With respect to the original boustrophedon decomposition, the Morse-based decomposition has the advantage of handling also non-polygonal obstacles. By choosing different Morse functions, different cell shapes are obtained, e.g. circular or spiked cells.

A new approach for cellular decomposition will be proposed here. Based on the Morse method, critical points can be determined. However, Morse method does not categorize the type of critical points. In this approach critical points are categorized into four groups as follows (Fig. 6) :

- Critical point IN type 1 (red circle) : the connectivity of a slice is increased by one and the obstacle is on the right.
- Critical point IN type 2 (blue circle) : the connectivity of a slice is increased by one and the obstacle is on the left.
- Critical point OUT type 1 (red square) : the connectivity of a slice is decreased by one and the obstacle is on the left.
- Critical point OUT type 2 (blue square) : connectivity of a slice is decreased by one and the obstacle is on the right.

The algorithm for decomposing the cluttered environment to cells is shown as follows :

- Step 1 : Use a vertical line and sweep it from the left to the right of the environment, and find all the critical points.
- Step 2 :
 - At each critical point IN type 1, draw a horizontal line to the left till when that line touches the obstacle or the border of the area.
 - At each critical point OUT type 1, draw a horizontal line to the right till that line touches the obstacle or the border of the area.

The results of the original boustrophedon method and the cellular decomposition of this approach are shown in Fig. 5a and 5b.

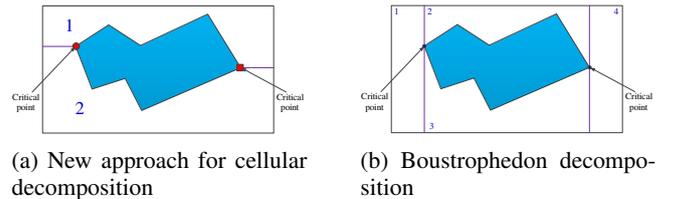


Fig. 5: Cellular decomposition methods

Simulation results analysis

This approach has been run and verified in Matlab. From Fig. 5a and 5b, one can see that with our approach, the area has been splitted into two cells compared with four cells of the Boustrophedon decomposition method. Area with complicated forms (convex, non-convex, polygon, and arbitrary shape) (Fig. 6) of obstacles has been splitted to only 9 cells by using the new proposed approach, compared with more than 20 cells if using Boustrophedon method.

B. Way-points generation and optimization of the percentage of coverage (WG-OSA in Fig. 1)

1) *Way-points generation (WG)*: As described in section II, picture frames which are taken by the camera mounted on

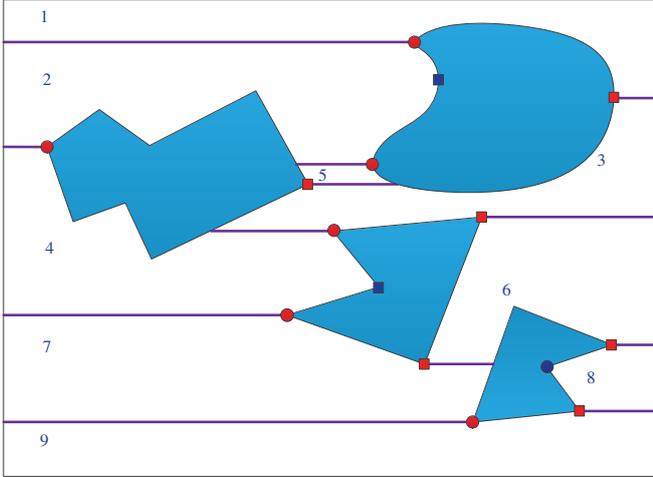


Fig. 6: New approach for Boustrophedon decomposition

the aerial robot are rectangular. Consequently, for gathering the whole area of the environment, frames need to be arranged as in Fig. 3. Centers of these rectangles are the positions of the UAV, in which the pictures will be taken. We can see that the set of all these points is way-points that the UAV has to visit.

Way-points are generated as follows :

- The first rectangle on the top left corner has the center with coordinate (X_s, Y_s) .
- Fill the whole working area with rectangles (Fig. 7) from the left to right and from the top to bottom such that two neighbor rectangles on horizontal direction have an overlapped rectangle area with dimension $dH \times L$, and two neighbor rectangles on vertical direction have an overlapped rectangle area with dimension $H \times dL$ (Fig. 3).
- Find coordinates of set X that consists of all the centers of rectangles which are located in the obstacle (Fig. 8).

2) Optimization of the percentage of coverage (OSA):

Optimization process is processed as follows :

- Calculate the non-obstacle area of all rectangles that have been created with center in X .
- Find the percentage of coverage and number of images needed for the coverage.
- By varying the coordinate of the first image, means that by varying (X_s, Y_s) such that $(X_s, Y_s) \in [1 \dots \frac{H}{2}; 1 \dots \frac{L}{2}]$, one can have the maximal coverage percent or minimal number or images needed to be taken.

Simulation results analysis

Simulations in this section have the following parameters :

- Image dimension : 1200×700
- Picture frame dimension
 - $H = 40; dH = 2;$
 - $L = 80; dL = 2;$
- trade-off function : $coverage_percentage \times (1 - \alpha) - no_way_point \times \alpha$ where $\alpha = 0.2$

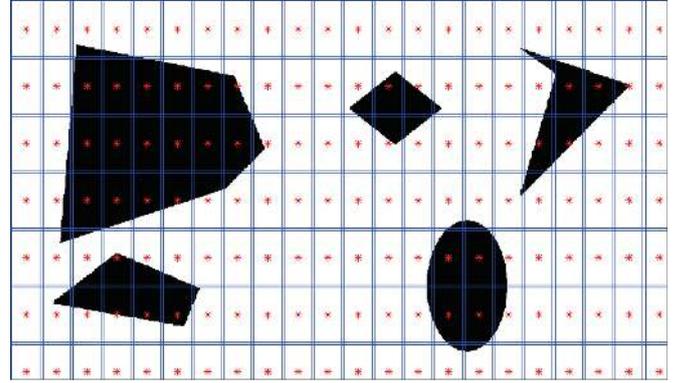


Fig. 7: Picture frames

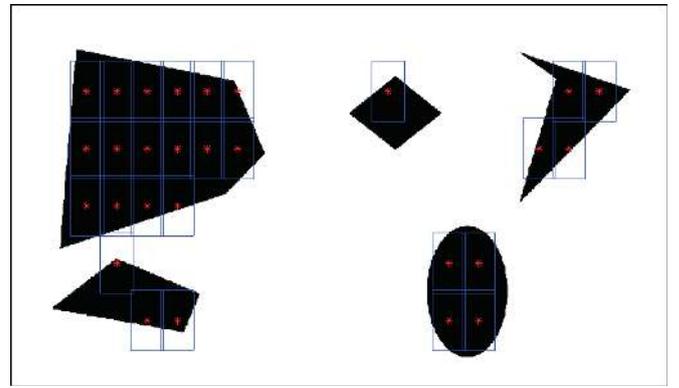


Fig. 8: Rectangles with centers in obstacles

TABLE I: Some results for simulations in Matlab

X_s	Y_s	Number of way-points	% coverage	Trade-off function
20	40	230	95.0196	30.0085
20	38	229	94.6407	29.8860
19	39	228	94.3653	29.8922
1	1	275	96.3794	22.1035
2	10	266	96.4520	23.9616
3	13	266	96.3549	23.8839

Simulations in this section have the following parameters :

- Image dimension : 1200×700
- Picture frame dimension
 - $H = 20; dH = 2;$
 - $L = 40; dL = 2;$
- trade-off function : $coverage_percentage \times (1 - \alpha) - no_way_point \times \alpha$ where $\alpha = 0.2$

TABLE II: Some results for simulations in Matlab

X_s	Y_s	Number of way-points	% coverage	Trade-off function
1	1	1044	97.5	-130.8
1	7	1048	97.8	-131.4
2	5	1030	97.9	-127.7
10	20	1026	97.5	-127.2
10	14	1031	97.9	-127.9
9	14	1029	97.8	-127.6

The simulation results given in table I show that, in the case when the dimension of images is large ($H = 40, dH = 2; L = 80, dL = 2$) the number of way-points

affects the percentage of coverage. However, with the same trade-off function, when the dimension of images is small ($H = 20, dH = 2; L = 40, dL = 2$), the percentage of coverage seems not to be affected by the number of way-points.

C. Optimized path planning generation (OPPG in Fig. 1)

Theoretically, it is possible to find the shortest traveling distance for all the way-points generated in the previous section. To do that, firstly, the distance between each two points needs to be calculated and the path between this two points has to avoid the obstacles. Several methods can perform that such as PRM or Rapidly-exploring Random Tree(RRT)[11]. For instance, if there are n way-points, the number of paths to be found is $\frac{n(n-1)}{2}$. After that we can use TSP for finding the shortest path between n way-points. However, the calculation time can be important.

For avoiding this disadvantage, this section provides another approach. Instead of applying TSP for all the way-points, first we will split the whole area to non-obstacle separated cell and each cell can be covered by simple back and forth motion (as has been proposed at the beginning of this section) by the UAV. Then, the TSP is applied only for finding the shortest path length for moving between cells.

In [8], the authors used the adjacency graph for finding the sequence of cells to be visited to cover the area. But this approach does not guarantee the order of visited cell gives the shortest path for changing between cells. In this section, we introduce a method for finding the cells' sequence with the shortest path length for changing cells.

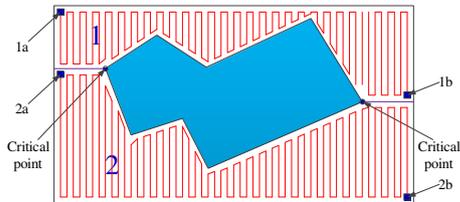


Fig. 9: In/Out points in each cell

As seen in the previous section, the working area was splitted into obstacle-free cells, and the UAV can make the back and forth motion to cover cells. Consequently, for each cell, there will be two points : initial and final for the UAV coverage (Fig. 9). For example, for $cell_k$, these two points are k_a and k_b . UAV can start covering the k th cell from point k_a to k_b or inverse from k_b to k_a .

Here each cell will form two nodes of the TSP such as two nodes $cell_{1_a}$ and $cell_{1_b}$ for $cell_1$. Consequently, if the UAV is in node $cell_{1_a}$, it has to go through node $cell_{1_b}$ and inverse. To do this, an additional constraint has to be added to the constraints of TSP for each cell :

$$x_{cell_{k_a} \rightarrow cell_{k_b}} + x_{cell_{k_b} \rightarrow cell_{k_a}} = 1 \quad k = 1, 2, \dots, 2n \quad (1)$$

The UAV starts at initial position (START), scan the whole area and go back to the final position (STOP) for charging the battery as shown in Fig. 10.

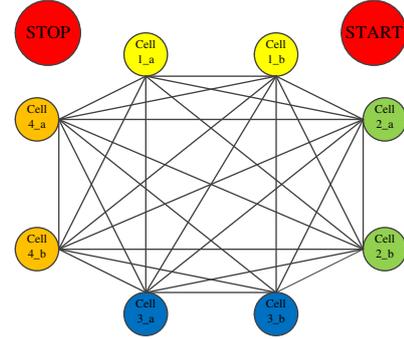


Fig. 10: Travelling Salesman problems with additional constraints for this problem

To ensure that there will always exist a solution for this optimization problem, the initial population for GA has the form as shown in Fig. 12. The flip, slide and swap operations are always operated on each pair of nodes x_a and x_b where $x \in [1, n]$. In each iteration, the random swap position of cell x_a and x_b is also processed.

The flip, slide and swap operations are described in Fig. 11b, 11c, 11a i, j such as $i < j$.

The advantages of using proposed flip, slide, swap operations as depicted above will make the search for optimal path faster because this search is performed only on the set of paths that satisfy the given request. Furthermore, the solution is always found even though with the number of cells is huge.

If proposed flip, slide, swap operations are not applied, the optimal path can only be found when the $number_of_cell \leq 16$, and the simulation time is always greater than 2000 seconds.

Simulation results as shown in table III were performed on a Dell inspiron 7559 with Core i7, 8Gb, Windows10, Matlab 2016b configurations specified in the table. The parameters for GA are : $population_size = 1000$; $number_of_iteration = 1e4$; $number_of_cell = 100$;

TABLE III: Time of simulation

Simu.	With proposed operations	Without proposed operations
1	732.8133 sec, solution found	> 3000 sec, no solution
2	743.4828 sec, solution found	> 3000 sec, no solution
3	742.2244 sec, solution found	> 3000 sec, no solution
4	742.6994 sec, solution found	> 3000 sec, no solution



Fig. 12: Genetic algorithm using in this approach

The algorithm is shown on Algorithm 1.

IV. CONCLUSION, AND FUTURE WORKS

In this paper, we have proposed a new approach for maximizing the coverage area and minimizing the path length of an aerial robot in agriculture environment with concave obstacles. Firstly, this paper developed a new approach for

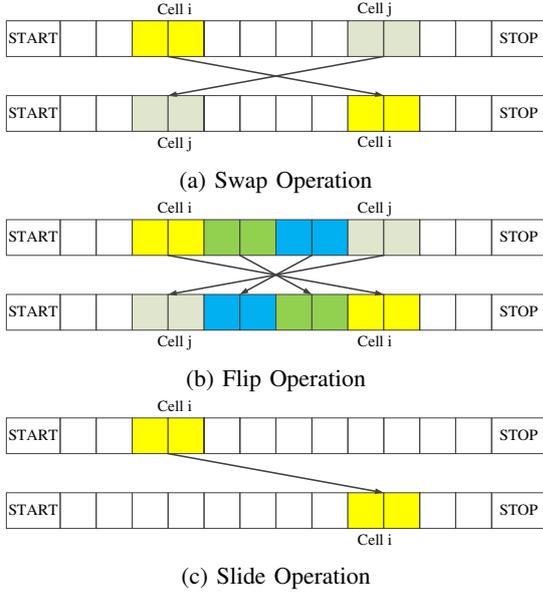


Fig. 11: Swap, flip, and slide operations for GA

cellular decomposition. Based on the critical points as in [8] and [9], the extension of this paper is that the critical points have been categorized to several groups, and the cells have been created from these groups. This extension leads to a decrease of the number of cells after decomposition. The results show that this new cellular decomposition works well even with several concave obstacles inside the environment.

Secondly, we have proposed a method for maximizing the percentage of coverage and we have given some comments for the trade-off between the percentage of coverage and the number of way-points for the UAV. The percentage of coverage is up to 97.9%.

Finally, by using GA with some modification on the swap, flip and slide operations and the TSP with some additional constraints, the shortest path for changing the cells has been developed. This algorithm guarantees that the solution always exist and the time for calculation is decreasing.

The results provided in this paper have been obtained under Matlab/Simulinks. The continuation of this work is to add the UAV equations of motion as constraints on the path. In the future work, firstly, the results will be verified in aerial platform. Then the efficiency of the algorithm will be improved to be real-time usable.

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Algorithm 1: Genetic Algorithm and Travelling salesman problem approach in this paper

input : instance Π ,
population size : $4 \times \alpha$,
number of iterations : δ

output: Solution X

Generate $4 \times \alpha$ feasible solutions randomly with the form as in Fig. 12;

Save them in the population Pop ;

$globalMin = \infty$;

for $i \leftarrow 1$ **to** δ **do**

// Update the best solution

Select the best solution $minDist$ in Pop ;

if $minDist < globalMin$ **then**

$globalMin = minDist$;

// Mutation

for $j \leftarrow 1$ **to** α **do**

// Mutate the best to get three new routes

Find the best solution bs on 4 solutions

$X_{4 \times j}$; $X_{4 \times j-1}$; $X_{4 \times j-2}$; $X_{4 \times j-3}$ of Pop ;

bs_1 is generated by flip bs from random elements I (node I_a and node I_b) to

J (node J_a and node J_b);

bs_2 is generated by swap random element I and J in bs ;

bs_3 is generate by slide bs from random element I to J ;

Two gens in elements I ($I \in [1, \dots, n]$) of bs_1 , bs_2 , and bs_3 can be randomly swapped;

Generate matrix T_j from 4 columns matrix bs , bs_1 , bs_2 , and bs_3 ;

// Updating

Update $Pop = T_1 + T_2 + \dots + T_\alpha$;

return the best solution X in Pop ;

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