

## A waypoint-based mission planner for farmland coverage with an aerial robot – A precision farming tool

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### Abstract

Remote sensing (RS) with aerial robots is becoming more usual in every day time in Precision Agriculture (PA) practices, do to their advantages over conventional methods. Usually, available commercial platforms providing off-the-shelf waypoint navigation are adopted to perform visual surveys over crop fields, with the purpose to acquire specific image samples. The way in which a waypoint list is computed and dispatched to the aerial robot when mapping non empty agricultural workspaces has not been yet discussed. In this paper we propose an offline mission planner approach that computes an efficient coverage path subject to some constraints by decomposing the environment approximately into cells. Therefore, the aim of this work is contributing with a feasible waypoints-based tool to support PA practices.

**Keywords:** Coverage path planning, Aerial robots, Quad-rotors, Remote sensing.

### Introduction

Mini aerial robots equipped with inexpensive and lightweight sensors have turned into a suitable Remote Sensing (RS) platform, fulfilling the lacks left open by other RS tools, such as satellites on airplanes, providing an affordable, flexible and fast way for agricultural data acquisition and delivery.

Aerial robots are mainly employed in agriculture for crop observation and map generation through imaging surveys [Johnson, 2003], [Herwitz, 2004], [Xiang, 2007]. The maps are usually built by stitching a set of geo-referenced images (i.e. orthophotos) through mosaicking procedures. Hence typically maps information about the biophysical parameters of the crop field.

Moreover, the agricultural experiments reported with aerial vehicles fall mainly in waypoints-based navigation [Johnson, 2003], [Zarco-Tejada, 2009], [Nebiker, 2008], where the aerial vehicles navigate autonomously through a trajectory predefined by a set of points in the environment.

Therefore, the aerial vehicle usually has to cover the full area to scan following a continuous and smooth trajectory while avoiding areas or parcels that are not objectives. It is also desirable to minimize the number of changes in direction and revisiting the minimum number of points. Furthermore, since not all areas are suitable for takeoff or

landing with Aerial Robots, the trajectory must ensure starting and ending points in places that fulfill all the requirements (safety margins, space enough for operation, pick up and drop ability, accessibility).

Coverage path planning (CPP) is a sub-field of motion planning, which indeed deals with techniques in order to determine the path that ensures a complete coverage (e.g. back and forth motions) for a robot in a free workspace. Since the robot has to fly over all points in the free workspace, the CPP problem is related to the covering salesman problem (CSP), a nondeterministic polynomial time hard problem [Choset, 2000]. Coverage path planning with Unmanned Aerial vehicles (UAV) is discussed in [Jiao et al., 2010] and [Maza & Ollero, 2007], are proposed exact cell decomposition methods to break down a polygonal area. Although the cited authors use an exact cell decomposition their approaches address mainly area decomposition and coverage with back and forth motions.

Herein we address the problem to cover an entirely farm site with a vertical takeoff and landing aerial robot, providing way-point navigation. Therefore an offline mission planner has been developed with the purpose to be used together with commercial off-the-shelf aerial robots. Our approach computes a coverage path restricted to the minimum number of turns and heading angles, avoidable cells, likewise predefined start and goal position.

## **Motivation**

Our motivation in the development of an offline mission planner based on way-points, is to improve the fact that up to now, most of the UAVs employed in agricultural management tasks, are off-the-shelf platforms with an autopilot that enables the user to insert a list of way-points.

The mission planner computes a coverage path given a target area and the a priori information therein. Therefore the user can use the mission planner to plan the path to cover with any type of aerial robot providing waypoint navigation, since the output is retrieved as a set of geographic coordinates. Therefore the feasible usage of the platform is maintained, odd from the focus and knowledge of its users.

## **Mission planner**

The workspace is decomposed through an approximate cellular decomposition, following the taxonomy proposed by [Choset, 2000], which means that the workspace is sampled like a regular grid. This grid-based representation with optimal dispersion is reached by dividing the space into cubes, and placing a point in the center of each cube, therefore can be defined has a kind of Sukharev grid [LaValle, 2006]. In this type of decomposition is normally assumed that once the robot enters a cell it has covered a cell, even by it footprint or end-effectors (see Figure 1).

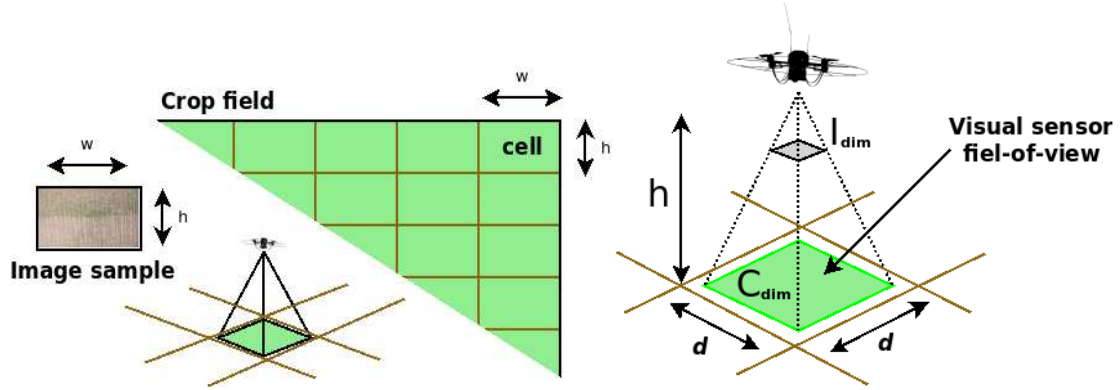


Figure 1 – Data acquisition in a grid-based decomposed environment.

Herein we consider that the center of each cell is a way-point, and each cell is an image sample, the cell dimension can be obtained through the following relationship,

$$\frac{C_{dim}}{h} = \frac{I_{dim}}{f} \quad (1)$$

Where  $C_{dim}$ ,  $h$ ,  $I_{dim}$ ,  $f$ , stands respectively to cell dimension in meters, flying height, image dimension, focal length of the camera. Should be said that the aerial robot has to fly at a certain constant height in order to ensure a determinate grid resolution and the image sensor field-of-view (FOV) should be enough to cover a cell with a predefined dimension, Figure 2 shows the relation between the cell dimension and the aerial robot height from the ground.

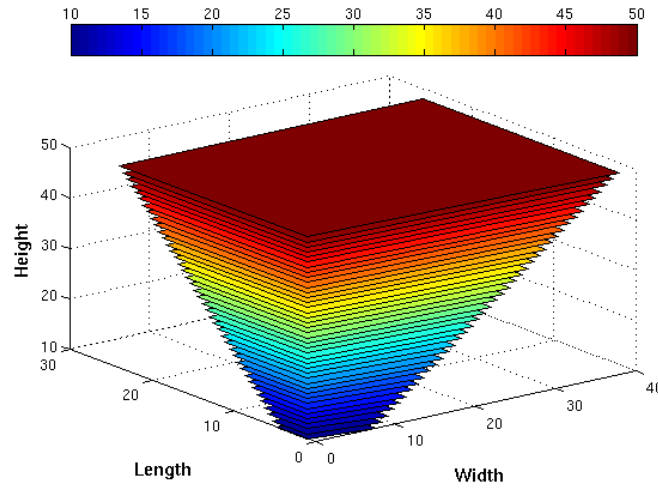


Figure 2 - Cell size example at several altitudes, considering a focal length of 50mm and a 135 film frame.

Another advantages of having a grid-based decomposition is that directly maps the robot workspace into a kind of unit distance graph, denoted as grid graph  $G_{\langle V, E \rangle}$  where  $V$  are the vertices and  $E$  the edges. Each vertex represents a way-point and each edge, the path between two way-points  $u$  and  $v$  such that  $u \sim v$ .

To ensure an optimal coverage time, we have to compute a coverage path that does not pass by any points in the environment twice, and at the same time, performs this

trajectory with the minimum number of turns. Thus we need to calculate the path cost based on how many times the aerial robot has to change its direction, or even how many rotations have to be done. In order to compute the number of turns, we can consider two types of neighborhoods, the Von Neumann 4-points connectivity and Moore 8-nodes neighborhood. If we consider a Von Neumann neighborhood, the aerial robot angle of turn is limited to  $\pm 90$ , instead if we choose a Moore neighborhood the robot will be able to turn  $\pm 45$ ,  $\pm 90$ , or  $\pm 135$ .

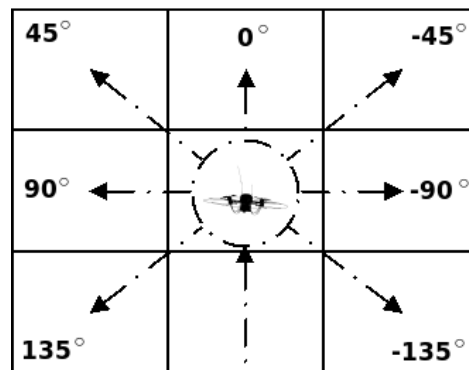


Figure 3 - Schematic with the possible drifts performed by the Aerial robot.

To find a complete coverage path that passes through all nodes in the adjacency graph just once, we apply a Deep-limited search (DLS) to built a tree with all possible coverage paths. By using this approach, we can limited the search length to the number of vertexes, and consequently, the search neither goes around in infinite cycles and nor visits a node twice. On the other hand, by using this blind-search procedure we will have an augmented number of solutions, and after computing all of them we still have to compute the number of turns for each one, which has a very high computational cost. For that motive we employ a heuristic-based approach based in a wave-front planner [LaValle, 2006]. The wave-front planner works by propagating a distance transform function from the goal cell through all free grid cells bypassing all obstacles (i.e. herein we assume that an obstacle is a cell, or even a set of cells that we not intend to visually cover).

The distance transform function is applied over the grid by employing a Bread-first search (BFS) on the graph induced by the neighborhood adjacency of cells, hence the coverage path can be easily found from any starting point within the environment to the goal cell, by choosing the nearest neighbor cell in gradient ascendant order, instead as usually, in gradient descendant order. During the gradient tracking, the algorithm is going to find more than one neighbor to choose from, with the same potential weight. Additionally, the bottleneck caused by the local minimal can also block the search. To solve those issues, we employ a backtracking procedure that keeps in memory all unexpanded child nodes, which have the same potential weight that other child nodes, from the same parent node. Furthermore as seen before the aerial robot can perform three different angles of turn in the grid-based workspace, since the real cost (speaking in terms of time to perform such movement) is not the same for each turn, e.g., is clear that the time requested for a change in direction of  $45^\circ$  is less than the time requested for a change in direction of  $135^\circ$ . Therefore, instead of just minimizing the number of

turns, qualitatively, we minimize also the sum of the heading turns performed, quantitatively, by weighting each robot rotation via a weight  $\Gamma$  as follows,

$$\Gamma_{135^\circ} > \Gamma_{90^\circ} > \Gamma_{45^\circ} > \Gamma_{0^\circ},$$

The sum of the heading rotation weights can be written as,

$$\Gamma = \sum_{i=1}^N \Gamma_k^i,$$

where  $N$  stand for the number of turns made and  $k$  the rotated angle. Finally, our goal is to minimize  $\Gamma$ .

### Application and results

In order to show the feasibility and applicability of the proposed approach, let's consider the othophoto taken from an agricultural field situated in the northwest of Madrid, Spain, with geographic coordinates  $40^\circ06'43.83''\text{N}$  and  $3^\circ17'01.14''\text{W}$  (see Figure 4). The blue line delimit the shape of the field and also the area of interest where we aim to acquire data. However, there are also some areas that we are not interested to sample, such like a couple of trees on the field, machinery, or even a parcel with a different cultivation. Those are represented by the red dashed line. Moreover, we must define the grid-based workspace boundaries, which is depicted in yellow.



Figure 4 –Target agricultural field to remote sensing with an aerial robot.

An user with access to a geographic information system (GIS), can easily obtain *a priori* information from the agricultural field that he/she wish to sample, and consequently this information is used to define the grid resolution, and also set the mission planner. The yellow lines delimit an area of  $63765 \text{ m}^2$  which correspond to  $195 \text{ m}$  length and  $327 \text{ m}$  width. Let's assume that the aerial robot carries a commercial digital camera that provides image resolutions up to  $10.4 \text{ mega pixels}$ . Moreover, we choose the best image resolution to sample the field, which correspond to an image size

from 3368x3088 pixels. If we wish to have a spatial resolution from 1 pixel/cm, we will obtain a grid resolution from 6x10 cells, where each cell will have approximately 1063 m<sup>2</sup>. Considering the last workspace resolution to carry out our goal, the following environment decomposition is obtained (see Figure 5). Moreover, Table 1 resume the information obtained *a priori* from the workspace.

<b>Corners coordinate</b>	<b>1</b>	40.113506°	-3.284718 °
	<b>2</b>	40.111889°	-3.285633°
	<b>3</b>	40.112345°	-3.281221°
	<b>4</b>	40.110729°	-3.282138°
<b>Size</b>	<b>Width</b>	195 m	
	<b>Length</b>	327 m	

Table 1- *A priori* information from the grid-based workspace.

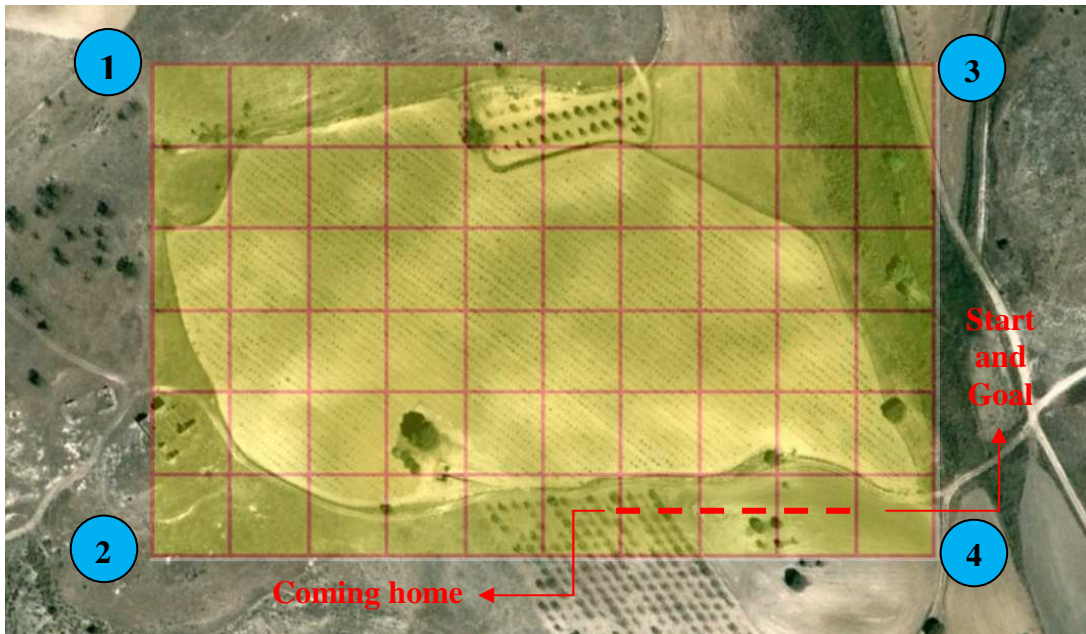


Figure 5 - Agricultural field decomposed approximately by cells with 32.7x32.5 m size.

Since the visual sensor is carried by the aerial robot, we must assign at which altitude it has to fly to provide those resolutions. As previously stated Equation 1 can provide the relation between the cells dimension and the sensor distance, given the characteristics from the visual sensor. Let's assume that the image dimension is 35mm and the focal length of the camera is from 50mm. In this way we obtain a horizontal and vertical field of view of 46.71 m and 46.42 m respectively. For that motive if we set the aerial robot altitude to 50 m it will be enough to map the area of each cell.

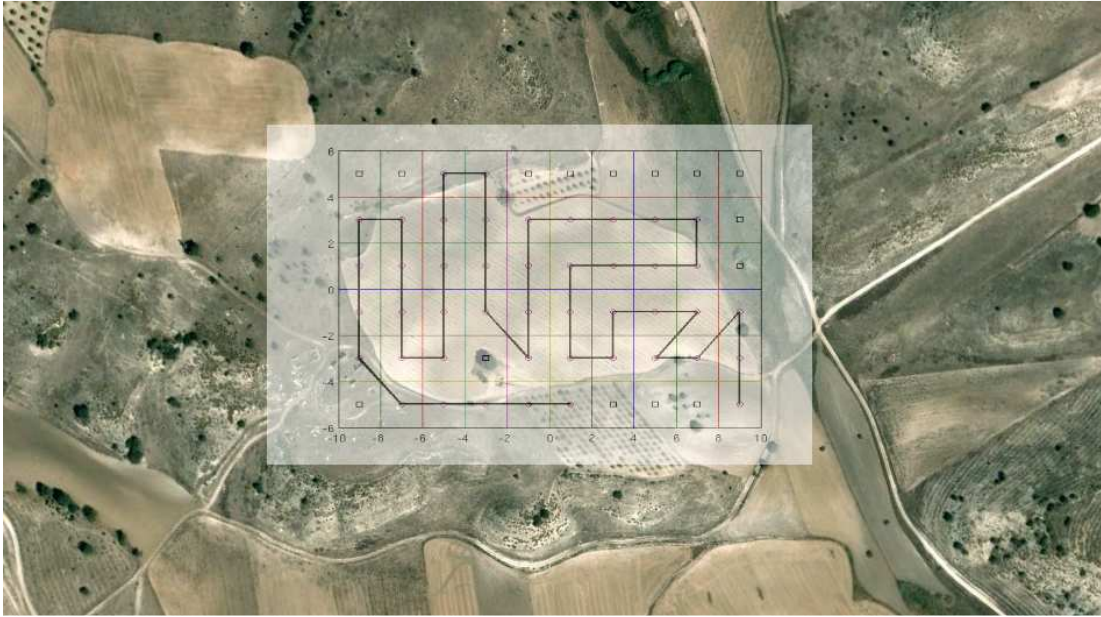


Figure 6 - Coverage path computed by the mission planner.

After setting up the mission planner with the information obtained from the GIS system and defining the start and goal positions, we will obtain the planned path depicted in Figure 6. The planner retrieve a coverage path with 21 turns which start and finishes in the bottom right corner of the workspace. The overall heading rotation cost can be express as,

$$\Gamma = 4 \times \Gamma_{135^\circ} + 13 \times \Gamma_{90^\circ} + 4 \times \Gamma_{45^\circ} + 28 \times \Gamma_{0^\circ}$$

The mission planner has been developed under Matlab. The example shown was computed in a Intel(R) Core(TM) 2 Duo CPU at 2.26GHz. A single best solution was then obtained over 420931 possible solutions in approximately 200 minutes.

## Conclusions

In this paper, a mission planner that computes a discrete coverage trajectory through waypoints, and also considers also regions of non interest to fly over is presented. The purpose of this approach is to provide with a visual coverage path of an agricultural field and employing aerial robots in a feasible fashion. In this way, this tool works out in three steps as shown in Figure 7: 1. Offline definition of the workspace and acquirement of datum from the GIS environment. 2. Insertion and computation of the coverage path based on the previous data. 3. Execution of the mission.

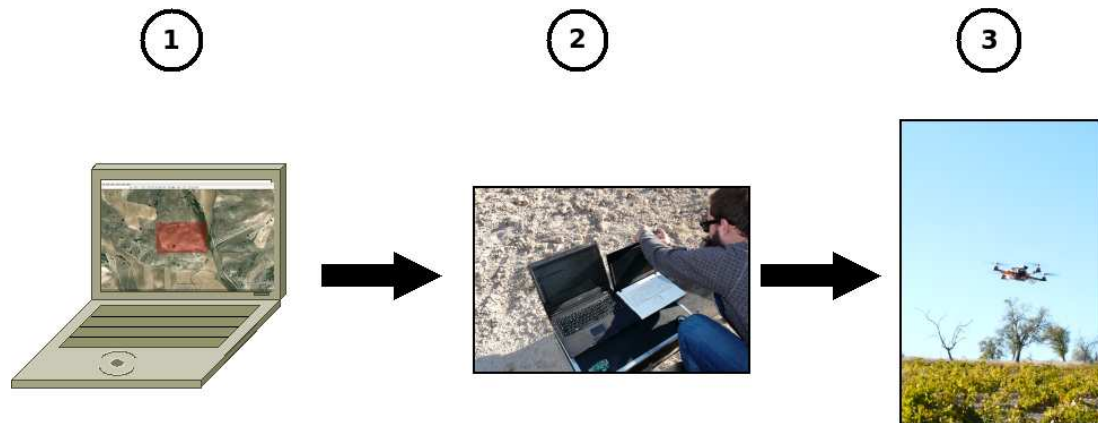


Figure 7 – The three step mission setup.

A drawback of our approach is the computation time imposed by the algorithm that looks up for the optimal path. However, since the mission planner works offline, this is not an issue during the execution of the experiments. In a future work, we will improve the algorithm to yield better computation time results. Furthermore, a multi-robot strategy will also be considered. A survey of a wide agricultural area with just one aerial robot might be an issue, since the current status of those small platforms still does not permit to perform long endurance missions. In this way, a fleet of aerial robots will play an important role in PA practices.

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