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Automatic Path Planning for Unmanned Ground Vehicle using UAV imagery

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Abstract. Field machines play an important role in the management of agricultural environments. Increasing use of automated machines in precision agriculture has gained significant attention of farmers and industries to minimize human work load to perform tasks such as land preparation, seeding, fertilizing, plant health monitoring and harvesting. Path planning is considered as a fundamental step for agricultural machines equipped with autonomous navigation system. For mountain vineyards, path planning is a big challenge due to terrain morphology and unstructured vineyards.

This paper proposes a workflow to generate an automatic coverage path plan for unmanned ground vehicles (UGVs) using georeferenced imagery taken by an unmanned aerial vehicle (UAV). First, image acquisition is performed over a vineyard to generate an orthomosaic and a digital surface model, which are then used to identify the vine rows and inter-row terrain. This information is then used by the algorithm to generate a path plan for UGV.

Keywords: Agricultural Field Machines · Automatic Coverage Path Planning · UAV Imagery · Unmanned Ground Vehicle · Photogrammetry

1 Introduction

Increase in use of the automated machines in agricultural environment has gained significant attention of farmers and industries to minimize human work load to perform related tasks. Automated vehicles need to have an automatic navigation system and they have to be able to autonomously select the path according to the specific area and obstacles. To increase agricultural productivity, path planning techniques have been implemented to cover the crop fields. In many cases, the crop field plots are planned with the knowledge of on-field expert for autonomous agricultural machines. Several advancements in path planning methods for agricultural productions using different optimization techniques for single or multiple coordinated vehicles which span the entire field, are discussed in [1]. For agricultural field vehicles, the greedy algorithms can be used to find an efficient route considering the required condition of covering the whole field [2].

For agricultural vehicles, path planning for known environments usually involves the partition of the area to cover in small polygonal regions called parcel, to find the best path for each parcel and then aggregate the results. Several optimization techniques have been implemented to find an approximate solution that solves the coverage path planning problem, such as neural networks [3] and genetic algorithms [4]. Due to widely available optimization techniques, selection of a suitable algorithm is an important step, for both path planning and modeling the environment.

Using high spatial resolution imagery (HSRI), the plantation, boundaries and inter-row terrains become distinguishable, providing capabilities to discriminate and characterize the area [5]. However, considering the capability of HSRI with automatic processes needs new image processing methods, allowing the analysis and classification of vegetative and non-vegetative pixels from textured image. Fast Fourier Transform (FFT) and Gabor Filtering have been discussed in [5–7], which permits to delimit vineyards and to determine inter-row width and row orientation. The main problem of this method is related to boundary precision in particular when missing plants are present.

This work proposes a workflow that automatically generates coverage path plan for UGV using high resolution imagery acquired from UAV. Study area and data acquisition related details are discussed in section 2 and 3 respectively. Data processing, mask generation and algorithms used in the study are discussed from section 4 to 8 followed by the conclusion and future work.

2 The Case Study

The survey was conducted in a rural area near the town of Baldichieri d'Asti (AT), in Piedmont. This hilly area, called "Basso Monferrato Astigiano", is dominated by forests and vineyards [8]. The area of interest, property of the "Azienda Agricola Ciabot", is around 2 ha. It is not flat and it is characterized by the presence of obstacles inside and outside the area. Indeed, in the area there are few small houses and it is rounded by woods.

Image acquisition and 3D model were generated for the whole area, instead the path planning was focused in a small area with only one obstacle, to test, as first step, the path algorithm in a simple real case (Figure 2).

3 Fieldwork and data acquisition for base map generation

The data acquisition was carried out in October 2018. Due to the specific exposure of the area that causes a lot of shadows, two campaigns of acquisition were carried out in the same day (at 10.30 am and at 5.00 pm). Due to the lack of natural points, 16 plastic targets were placed on the ground, Ground Control

Points (GCPs), to allow the model georeferencing. The coordinate of each target were measured using a Network Real Time Kinematic (NRTK) Global Navigation Satellite System (GNSS) technique [9]. The NRTK survey was performed by a SP80 Trimble GNSS receiver, using the real time correction of the permanent GNSS station of Canelli.

The UAV was chosen according to the size of study area, flight time and expected output of the survey. The used platform was a DJI Phantom 4 Pro, equipped with a RGB camera with focal length 8.8 mm, CMOS sensors 13.2 x 8.8 mm, pixel size of 2.4 m. The flights were planned using the open source software Mission Planner that connects the platform to the ground station. This tool was also used to set all the parameters of the flight plan, configuration of the flight (nadir images in North-South direction), height of the flight (33 m to have a Ground Sample Distance, GSD, of 8 mm) and the overlap between different images (80% longitudinal and 60% transverse overlap).

The duration of each flight was about 15 minutes and a total of 261 images for the first flight and 209 images for the second flight were acquired.

4 Data processing and validation

The data processing consists on the 3D model generation to extract the orthophoto, the Dense Digital Surface Model (DDSM), and the Dense Digital Terrain Model (DDTM) [10]. The data processing was performed with the commercial software Agisoft PhotoScan 1.2.6. For each flight, all the images acquired were processed in a single block, following these steps: alignment and orientation of the cameras, images georeferencing by GCPs (horizontal and elevation accuracy are less than 2 cm), point cloud densification (about 80 million points) [11]. From the dense points cloud, the standard workflow of the software allows to generate the mesh and the DDSM. However, in this case a further step was made to generate also the DDTM. The software, by the "*Classify ground point*" tool, allows to perform a unsupervised classification of the point cloud to detect only the points on the terrain surface [12]. The classification was performed based on three main parameters:

- max angle: maximum slope of the ground within the scene (20°);
- max distance between the point above the ground and terrain model (0.05 m);
- cell size of the largest area that does not contain any ground points (1 m^2).

Each parameter was chosen according to the features of the area described in section 2. The outputs of the whole procedure are DDTM, DDSM and an orthophoto in raster format with a cell size of 0.02 m, in WGS84 UTM 32N coordinate system.

5 Mask generation for path planning

This step aims at the definition of a binary image where nonzero-value pixels represent vineyard lines, building and all the potential obstacles for the UGV path. A methodology based only on a 3D geometric information was developed. The map with potential obstacles and vineyard lines was carried out by an approach that considers the differences between DDSM and DDTM. This step was performed with the commercial software ArcMap using the "*Raster math-minus*". After that, the final map was obtained classifying the differences into two classes (greater than 0.50 cm, and smaller than 0.50 cm). Using the "*Raster Reclass*" tool, non-zero value was assigned to the differences greater than 0.50 cm which represent the presence of obstacles and zero value to the differences smaller than 0.50 cm which represent the ground. The process was applied to the data of both flights and the masks were merged to obtain a complete information.

6 Steps to generate path plan

In the study area, there are three vineyard fields (Figure 2), hereafter called parcels. Proposed algorithm automatically generates a path plan, which the UGV has to follow to cover a parcel.

A generic approach has been followed to develop the algorithm for kind of crops having considerable inter-row spacing for the UGV movement. The flowchart in Figure 1 summarizes the adopted approach to develop the algorithm.

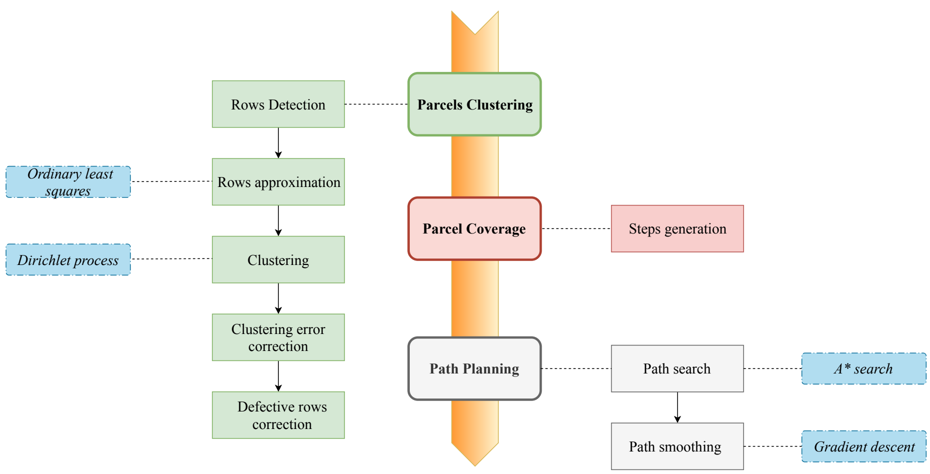

Fig. 1: Workflow.

7 Parcel recognition and rows clustering

The first step of the algorithm deals with the detection of the rows that compose the vegetation. Each group of interconnected black pixels represents one canopy row cluster. The algorithm is based on the idea of visiting all the mask (section 5) using a sliding window: starting from the first pixel in the upper left to the last pixel on the bottom right. The sliding window is defined with a proper width called ρ, which depends on the type of vegetation density. To take into account the possibility of having different distances in accordance to the plantation type a threshold value for ρ is required: for example, maize rows are closer to each other with respect to vineyards, where vine rows are more distant. In the environment under investigation a $\rho = 7$ pixels has been used. As the acquisition was performed after the harvesting season of the vineyards, therefore, some missing part of the vine rows were detected during the clustering and mask generation process.

When dealing with more than one parcel per map, it may occur that two of them are separated by a narrow path where the farmer or the vehicle have the possibility to pass. For this reason, the problem is twofold and it is necessary to recombine only the segments that effectively belong to the same row. The idea is to perform the linear regression of every row, finding the line that best fits each cluster. Ordinary Least Squares (*OLS*) method has been chosen to make the parameterization. It determines the parameters of a linear function given a set of variables: it minimizes the sum of the squares of the differences between the observed dependent variable in the given dataset and those predicted by the linear function.

As the canopy rows are, generally, disposed as straight lines, the most recurrent form is a first order polynomial. Due to the limitation of the model, if the points to be approximated are distributed along a vertical line and the variance occurs mainly in the horizontal direction, the *OLS* will not perform a good parametrization of the model. The problem occurs mainly because the *OLS* is designed to fit points with varancies in the vertical direction. To solve this problem, before projecting the data points into the *OLS* space, a rotation of 90° has been applied to the clusters which presented such *verticality*. Once all the rows have been identified, they need to be separated and grouped in parcels.

It is necessary to find a criterion which can be used to properly correlate only the rows of the same parcel, avoiding as much as possible errors.

Analyzing the literature [13, 14], the biggest problem encountered is related to the fact that the number of parcels within a field is not known a priori, unless the final user provides this information to the algorithm. For this reason the simplest algorithms or very hardware-demanding, such as *K-means* or *DBSCAN*, have been discarded [15, 16], deciding to implement clustering using the *Dirichlet Process* model.

Considering parcels separated by a free space of higher dimension with respect to the inter-row distance belonging to the same parcel, it is possible to use their *slope* to identify them uniquely. The result will be a collection of slopes close to each other if they belong to the same parcel. Due to the presence of different slopes, the resulting statistical distribution of angular coefficients will be in general multimodal. The assumption that all the data are generated from a mixture of finite number of distributions with unknown parameters allows to exploit the *Dirichlet Process*. At first hand it seems that slope feature is not enough restrictive to bind together the right rows. To solve this problem a further feature must be included, which can correlate the rows according to their mutual position: from each row the coordinates of its mean point have been picked, in such a way that distant mean points are unlikely to be recognized as part of the same cluster.

A drawback of this method derives from the fact that labelling errors can occur, affecting small piece of land where rows are not contiguous. The labelling correction has been performed by considering the majority of row's neighbors. This procedure is repeated recursively until no more label changes are present. The connection of two contiguous rows is done by extending the approximating line from the row's extremes until the neighbour is reached(Figure 2).

8 Steps generation and path planning

To guarantee the coverage, the UGV needs to receive some nodes along the path between the starting position and the goal.

A possible solution to this problem is to exploit the line which best approximates the row and the distance between two close rows. With these information a grid that contains the parcel can be created, whose dimensions must be such that the robot can navigate free of incident. Hence a safety distance must be included when it is built. The rows are extended in both directions of at least the dimensions of robot in such a way that it can perform the curve. Then the average point is computed, meaning that when the robot will end to perform the curve, it will lie exactly in the middle of the two rows.

It is still necessary to define the order in which the robot must cover them. A sorting function has been developed: it minimizes the *euclidean* distance between the current position and the following one. According to the needs it can be used either to cover all the parcels which compose the map or only the single parcel.

The planner is then developed by implementing the $A*$ algorithm [17], which uses as starting and goal nodes the points generated previously, and determines the optimal path between them avoiding obstacles. Then a smoothing of the $A*$ trajectory is performed with the first-order iterative optimization *Gradient Descent* algorithm.

9 Conclusion and future work

In this work, an automatic coverage path planning for UGV for hilly vineyard environment is proposed. UAV imagery is used to obtain a DDTM and a DDSM, which are used to build the mask for the path planning. The experimental results show that the work as a whole presents some significant contribution in coverage path planning for UGV in the challenging environment like hilly vineyards that can be useful for the farmers to manage agricultural tasks.

However, we found some weaknesses when dealing with environments that deviate significantly from one parcel to another in the considered study area.

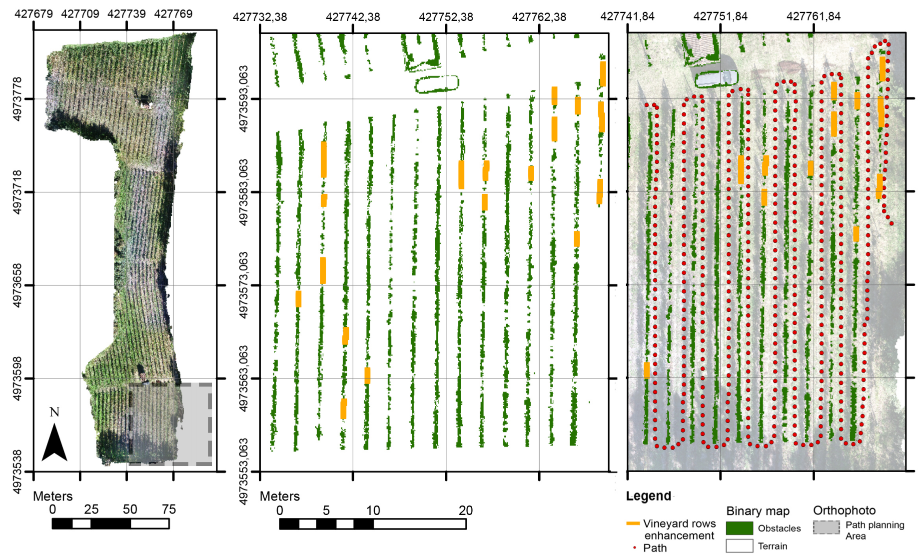

Fig. 2: Case Study. From left to right: overview, vineyard enhancement, path plan.

This can be dealt by considering one parcel at a time as we did in this work. In future, the same approach can be applied and tested with different vineyards fields and by considering the acquisition campaigns in accordance with the peak phenological stage of the vineyard.

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