MAPPING AGRICULTURAL AREAS USING AN AUTOMATED UNMANNED AERIAL VEHICLE

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ABSTRACT

Mapping procedure consist an essential operation towards fully automated navigation within any operational environment. This paper focuses on the development of a system, as a first approach, for the one-way communication between an unmanned aerial vehicle (UAV) and an unmanned ground vehicle (UGV) for the detection and registration of operational environment entities and the extraction of the geographical coordinates as a basis information for the subsequent automated navigation of the ground vehicle. The case study took place in a commercial orchard installed with walnut trees located in Central Greece. As a mandatory scenario for the tree's identification, was characterized the hypothesis of distinct, arranged circle like trees' vegetation within the field. The developed system consist an inaugural process towards fully automated operations in agricultural fields. In addition, it contributes to the two-way communication between autonomous vehicles (UAV-UGV) focusing on collaborative predictions and actions for both pre-planned and real-time planning processes.

Keywords: UAV, UGV, Precision Agriculture, Mapping, trees identification, path extraction.

1. INTRODUCTION

The rapid development of technological advances, in recent decades, led to the implementation of innovative systems into production processes. Supervisory control systems have been developed and implemented in various application areas (Colomina and Molina, 2014; Quintin et al., 2017). With the incorporation of the above in agricultural production, the concepts of «precision agriculture» and «agriculture 4.0» have been introduced (Weltzien, 2016; Ozdogan, Gacar and Aktas, 2017; Rose and Chilvers, 2018). In contrast to traditional agriculture, precision agriculture constitutes a comprehensive concept which aims at better management of the fields applying the right amount at the right place and time. The use of autonomous robotic systems is intended to assist in processing operations which are vital for the growing season (Pedersen et al., 2006; Mousazadeh, 2013; Bechar and Vigneault, 2016). To further explore, the use unmanned aerial vehicles (UAV) and unmanned ground vehicles (UGV) is documented to be a promising approach with a main objective of mapping field and crop properties. In tandem with computational efficiency and state of the art sensors, the implementation of the high-resolution cameras in UAV systems facilitates the incorporation of pattern recognition algorithms.

Previous studies on the identification of crop rows used pattern recognition methods. Initially the mosaic was transformed into gray-scale, to prevent the shading effect, and then the Hough transformation was implemented (Jiang *et al.*, 2016; Zhang *et al.,* 2008). Numerous methodologies were developed incorporating machine learning algorithms. Yang *et al.*, (2009) developed a framework which utilizes the Adaboost algorithm (Freund and Schapire, 1997) to identify trees from aerial images. Guerrero *et al.*, (2012) followed a different approach for the trees identification problem with the use of Support Vector Machine algorithm (SVM) combined with Otsu method (Otsu, 1979) to transform RGB grayscale images in order to distinguish the areas of interest (crop rows).

More recently, the potential benefits of the point cloud data exploitation were analyzed. (Torres-Sánchez et al., 2018) proved that the use of point cloud data potentially offers satisfactory results. Taking advantage of the altitudinal variations in an orchard in conjunction with OBIA (Object Based Image Analysis) algorithm (Blaschke, 2010) produced satisfactory results in recognizing trees from aerial images.

This paper focuses on the development of an autonomous system that uses the rapid mapping capabilities of unmanned aerial vehicle (UAV) for mapping agricultural large-scale areas and defines the path for the navigation of unmanned ground vehicles (UGV). In particular, the aim of this work is to identify and export areas (with accurate geographical coordinates) that denote collision free navigation for UGV within an agricultural environment (orchard). The challenge in this methodology is to correctly identify the trees in the outline of the field to properly export the required paths that the UGV should follow.

2. METHODOLOGY

2.1 Experimental Procedure

The experiment took place in 2018 in a commercial walnut orchard located in Rizomilos, Magnesia, Central Greece. The orchard was flat and there were no significant geomorphological variations. A DJI S1000+ octacopter (SZ DJI Technology Co., Ltd., Shenzhen, China) equipped with Pixhawk 2.1 autopilot (Proficnc®), Here+ GPS (Proficnc®) and Sony Cyber-shot RX100 III digital camera (SONY, Minato, Tokyo) was utilized to execute automated flights over the orchard. Initial test flights occurred in order to ensure the quality of the data and the proper execution of the experimental procedure. After the fine tuning, the landscape front lap and portrait side lap were set to 75% and the relative altitude was set to 40m providing ground resolution of 0.9 cm/px.

The unmanned aerial system (UAS) took pictures from the field using the survey technique with the QGroundControl. According to this technique, the spatial placement of specific distance points (based on the overlapping percentage) took place across the field. The collection of data required for the development of the algorithms was carried out at two different stages of the walnuts development, during August (walnut filling stage) when the canopy was fully developed and November (post-harvest) when the leaves were brown and the trees were defoliating.

2.2 Data Preprocessing

As a first step to the pre-processing procedure is the image geotagging. To that end, a linux shell script algorithm was developed to extract the UAV's position for each point of interest from the UAV's log file. Subsequently, all the geographical coordinates were assigned to the aggregated images. The Pix4Dmapper software suite was utilized for creating two-dimensional and three-dimensional field representation models.

The essential function of the algorithm was to identify and export points of interest within the field that denote the free movement of a UGV. For this purpose, a georeferenced ortho-mosaic was required. As a result, the geographical coordinates of both the orchard trees and the aforementioned areas were exported. In addition, a two-dimensional gray scale map was produced, which contained the reference points of a relative coordinate system for defining the UGV distance range. The produced map contributes to the autonomous navigation of the UGV using the Robot Operating System (ROS).

The proposed algorithm consisted of three distinct steps; a) mosaic's color transformation, b) trees Identification and c) path extraction.

In orchard fields, the emergence of vegetation of non-cultivated plants (weeds etc.) is quite common. This results in the occurrence of noise in the data. To address the phenomenon, a mosaic RGB transformation function was developed to the following color spaces to eliminate this noise and distinguish the trees from the weeds and the shadow effect. Three color transofmations were examined; HSV, YCbCr, and CIE L * a * b *. The HSV transformation provided better results compared to the other two transformations. In particular, using this transofmation the shading phenomenon and vegetation areas are distinguishable by the color code assigned to them. The YCbCr transformation provided better results for the images acquired in August, however, the results for the November images were quite poor. Therefore the HSV was selected for further analysis.

As a next step, a proper color filter was selected in order to disentangle the cultivated trees. Two basic color categories dominate the orchards' transformation in the color space. The areas of interest were isolated from the rest of the orchard. This process was performed on a function that takes an RGB image as an input, converts it into HSV, isolates the areas of interest, and applies the areas of lower interest to the original photograph.

The final step of mosaic's color transformation was to delete the noise and transform the mosaic into grayscale. A function was modified and incorporated for the elimination of noise and gray scale transformation leading to the final mosaic.

The Circular Hough Transform (CHT) technique was used to identify the orchard trees. A function was developed to calculate the CHT, taking into account previous work (Illingworth and Kittler, 1987; Manzanera et al., 2016). The shape of the final mosaic consists of grayscale pixels and non-compact circles (circle-like points). To identify circles with various R values, the iterative method was used to determine the radius of each potential cycle. To ensure proper identification of trees in environments with increased noise, a function was developed that recognizes the noise in the identified clusters based on their area. The area of the clusters followed normal distribution, with the area of the actual trees belonging to the interval [μ-σ, $\mu + \sigma$] where μ is the mean value of the areas and σ is their standard deviation. Therefore, any area smaller than the domain was defined as noise and was excluded (Figure 1). For the images taken in November, the noise level was considerably higher due to the trees defoliation and the decolorization of the leaves.

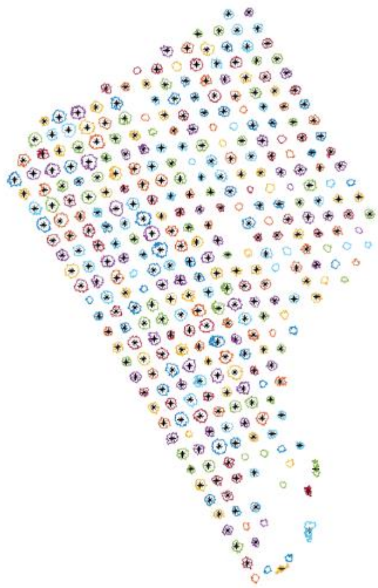


Figure 1. Identified trees, location and canopy shape, after the application of the noise depletion function in the ortho-mosaic.

Subsequent to the coordinates' transformation was the creation of virtual trees. Hence, a function was developed that takes into account the trees' arrangement in order to create trees in places where trees should exist (Figure 2).

For the path extraction, the combination of virtual and identified trees was used. To define the path, the mean distance between the tree rows was used. To properly classify the identified trees into their rows, an alignment was required.

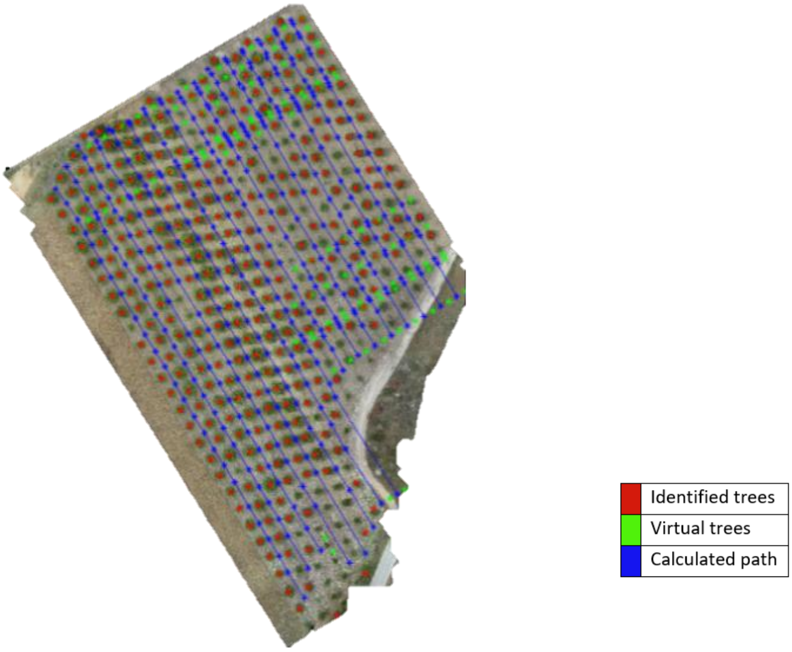
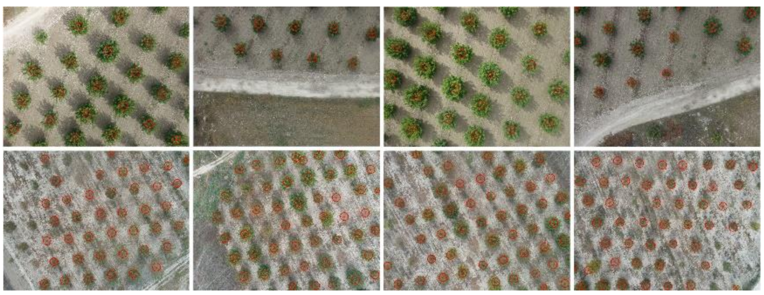


Figure 2. Path extraction using the ortho-mosaic from the walnut orchard in the study.

3. Validation and Results

The algorithm was validated using images from areas of the field with increased noise due to the occurrence of developed weeds in a significant proportion of the orchard's surface. The system performed well recognizing the vast majority of the trees (Figure 3).



a b c d

Figure 3. Trees identification validation for the aerial images acquired in August (top) and November (bottom) in four selected locations within the orchard with increased noise.

The actual location of the trees was manually recorded for ground truthing. The results from the developed image analysis procedure were compared with the manually recorded tree locations. The tree recognition rates were satisfactory, varying from 88.8% to 100% for the images taken in August. The recognition rate for the November data set was considerably lower, ranging from 78.4 to 94.1%, due to the partial defoliation of the trees, the color change of the leaves (turning brown) and the increased noise (Table 1).

Table 1. Accuracy of trees recognition using the developed image analysis algorithm for images taken in August and November.

ID	August	November
a	90.9	78.43
b	100	94.11
c	88.8	89.83
d	100	82.75

The path generated form the developed methodology for image analysis was used by the UGV to navigate in the orchard. The UGV followed the path without facing any issues and managed to avoid all the obstacles in real field environment. This was an indication that the UAV-UGV synergy is feasible and the two platforms can exchange data and information efficiently. The study is on-going and further tests in real field conditions will take place to confirm this outcome.

5. Conclusions

The nature of the operational environment in orchards is governed by unpredictable factors that introduce noise and contribute to the alteration of the requested data. The weather conditions combined with the cultivation practices and the constantly changing environment within the orchards during the growing season, bring changes in the tree phenology and the morphology of the soil surface. all these factors introduce different levels of noise in the images acquired form the orchard depending on the acquisition timing.

The development of a pattern recognition algorithm produced satisfactory results while minimizing computational costs since it required relatively small datasets. In addition, it allowed easy modification of the algorithm for various case studies. A major disadvantage of this method was the response to images with a lot of noise.

UAVs consist a rapid means for field scouting and monitoring making them an excellent tool for draw alternative routes for obstacle avoidance by the UGVs in the field. This type of UAV-UGV synergy is promising and may increase the efficiency of autonomous vehicles for in-field operations.

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