# Combined UGV and UAV perception of field areas as operational environments

**Vasileios Moysiadis, Dimitrios Katikaridis, Giorgos Vasileiadis, Damianos Kalaitzidis, Panagiotis Papazisis, Aristotelis C. Tagarakis, Dionysis Bochtis**

[1]Institute for Bio-economy and Agri-technology, Center for Research and Technology Hellas, Greece

v.moisiadis@certh.gr, d.katikaridis@certh.gr, g.vasileiadis@certh.gr, damianos.kalaitzidis@hotmail.com
panagiotis60@outlook.com, a.tagarakis@certh.gr, d.bochtis@certh.gr

#### Abstract

Detailed information of the structure of the surface in the extremely demanding and continuously changing environment of agricultural fields is essential for the automated navigation of unmanned ground vehicles (UGV). Unmanned aerial vehicles (UAVs) can rapidly provide essential information for this purpose. Hence, in this work the conceptualization of an inter-communication system UAV and UGV communication is proposed. The aim of the developed system is the cooperative UAV - UGV path mapping procedure for large-scale areas in tandem with the depletion of the operational costs related to the operational environment awareness. In order to accomplish the above-mentioned concept, state of the art technologies and algorithms were incorporated. According to the concept, the UAV executes an automated flight, detects the cultivated trees, extracts their coordinates and sends them to the UGV. As a final step, the UGV creates a pseudo 2D map with all the identified trees and the path to follow during the operations in the field. The developed system was tested in real field conditions in a commercial walnut orchard providing satisfactory operation.

**Keywords:** perception mapping, autonomous navigation, UAV, UGV

## 1. Introduction

With the introduction of Agriculture 4.0 concept, innovative technologies from numerous scientific areas have been implemented in order to facilitate the traditional agricultural methods (Weltzien, 2016; Ozdogan, Gacar and Aktas, 2017; Liakos et al., 2018; Angelopoulou et al., 2019). In tandem with operational efficiency, robotic systems (both ground and aerial) aggregate towards a promising alternative to the traditional intra-logistic operations within the field. For the purpose of the above, an essential step has to take place. The mapping procedures constitute a cornerstone towards fully automated operations that take place in outdoor operational environments. To cope with the abovementioned structure, various in-door mapping algorithms used by unmanned ground vehicles had been amended. The geomorphological divergence between the indoor and the outdoor environment along with the imponderable factors (weather, constantly changing environmental conditions, large-scale areas) that occur in the agricultural environments led to the deployment of the unmanned aerial vehicles for agricultural use.

Mapping of the physical environment of agricultural fields constitutes an essential operation towards the automated navigation of robotic technologies within agricultural operational environments (Bochtis et al., 2009, 2015; Kurashiki et al., 2010; Hameed et al., 2012; Hansen et al., 2013; Tokekar et al., 2016). Dynamic technologies are implemented to cope with the large-scale, in terms of area, and extremely demanding agricultural environment which is constantly changing. To that end, state-of-the-art technologies from various scientific fields have already been assimilated under the auspices of Agriculture 4.0. Additionally, the constantly increasing available computational power facilitates the development of Deep Learning (DL) methodologies in various agricultural applications to support farm management practices.

Numerous studies were conducted in the area of tree identification. Yang *et al.*, (2009) proposed a system that uses Adaboost algorithm to detect trees from aerial images. The fine-tuning of the Adaboost algorithm was took place in the work of (Greenberg, Dobrowski and Ustin, 2005). As a pre-processing method, all the imported images were transformed to the CIE L*a*b* color space to eliminate the shadow effect. Finally, they proposed a localization method in order to estimate the actual size of the identified tree.

The work of Amorós López et al. (2011) proposed a system for citrus grove identification and localization. The proposed method included the incorporation of RGB and NIR images as input for the trained model. Moreover, three machine learning methods were tested in order to optimize the produced results; a MultiLayer Perceptron neural network (MLP) (Duda, Hart and Stork, 2001), a Classification and Regression Tree (CART) classifier (Breiman et al., 2017) and a Support Vector Machine algorithm with the latter delivering the most accurate results.

In this study the conceptualization of an inter-communication system for UAV and UGV communication is proposed. The developed system provides the cooperative UAV - UGV path mapping procedure for operational environment awareness by the UGV. Preliminary test of the system performance took place in a commercial walnut orchard.

## 2. Methodology

The field work for data collection and system validation took place in 2018 and 2019 in three commercial walnut orchards located in Magnesia, Central Greece. The orchards were flat and there were no significant geomorphological variations. The first step of this work included the data aggregation for the training of the model to be developed. The eBee+ drone (fixed wing) was used to aggregate all the necessary data. The eBee+ (SenseFly, Switzerland) was equipped with an RTK GPS and a high resolution RGB camera (S.O.D.A., SenseFly, Switzerland). The UGV used in this work was the Husky robot (Clearpath Robotics, CA).

A machine learning algorithm was trained in order to identify the cultivated trees. The produced model was integrated in a Raspberry Pi along with an RGB camera. The overall scope of this sub-system was to take as input the real-time feed from the RGB camera and to export the position of the trees. Finally, a two-way communication between the UAV and the UGV was developed. Furthermore, an algorithm was developed and integrated into the UGV's computer for processing the aggregated data and creating the pseudo 2D map. The whole procedure of the proposed system is described in figure 1.

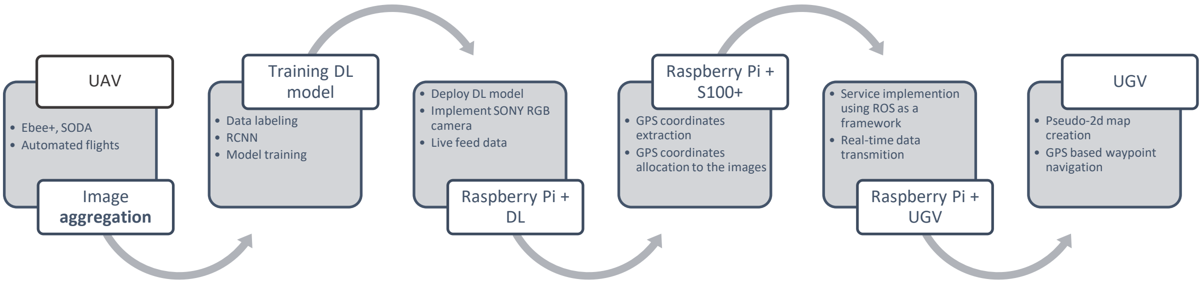


**Figure 1. Flowchart of the proposed system**

## 2.1 Image Aggregation

In order to aggregate all the necessary data for the model training, numerous automated flights took place at the walnut orchards (***Figure 2***). The collection of data required for the development of the model carried out at three different stages of the walnut's development, during May after leaf growth, November when the leaves were brown and the trees were defoliating (post-harvest), and December during dormancy when the trees were fully defoliated.

**Figure 2. UAV flight plans for the three commercial walnut orchards used in the study**

## 2.2 Software Implementation

### 2.2.1 Deep Learning algorithm

During the data acquisition process 1869 images were acquired in total from all three fields and development stages (August, November, December). All the datasets were aggregated. The 75% of the images were manually classified and used for training and the 25% for testing purposes.

The proposed system utilizes fast RCNN algorithm for identification and localization with ReLU as an activation function and 100 epochs. Moreover, as a pre-processing method, all the images were converted to the HSV color space to disentangle the image entities.

### 2.2.2 Raspberry Pi

The trained model was deployed in a raspberry 3 which was connected to the RGB camera. Live feed from the camera was transferred to the raspberry Pi in order to enable the trained model to identify the walnut trees. To further explore, the position of the UAV was transferred to the raspberry from the Pixhawk autopilot.

An algorithm was developed to assign coordinates to each pixel of the image and to correlate the points of interest (areas within the image with the identified trees) with the generated coordinates. Finally, with the use of the Robot Operating System (ROS) and a compatible package (mavROS) to incorporate the telemetry protocol which is used by the UAV to communicate with the ground station. the extracted coordinates from the identified trees were transferred to the UGV.

## 2.3 HARDWARE IMPLEMENTATION

To validate the proposed system, modifications in a UAV was took place in order to be equipped with the Raspberry Pi and be able send the necessary data to the UGV. All the autonomous flights were executed as a survey with the QGroundControl. The 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 and acquire high resolution (0.9 cm/px) RGB images

In order for the data to be obtained properly, a ROS service was developed within the UGV's ROSMATER. The service required a simple Boolean handshake in order to initialize the data transition. This is a real time approach according to which, as the trees are identified by the system they are instantly arranged in space in order to create the psedo-2DMap with the tree positions.

The UGV used in the study was the Husky robot equipped with RTK GPS (with 10Hz position refresh rate), IMU and a 3D Velodyne laser scanner for real-time obstacle avoidance. The system was tested in real field conditions to evaluate the communication between the UAV and UGV and for the proof of concept of the study.

## 3. RESULTS AND DISCUSSION

To validate the proposed system, images from all three walnut orchards were aggregated to examine the accuracy of the system in orchards with different properties. The actual location of the trees was manually recorded and used for ground truthing. The results from the developed image analysis procedure were compared with the manually recorded tree locations.

**Figure 3. Trees identified by the developed system for the image acquired during (a) May, (b) November and (c) December**

In the dataset of the images acquired in May, when the canopy was developed, the algorithm responded very well identifying the trees with high accuracy (100%). The tree recognition accuracy was adequate, but considerably lower compared to the May results, for the November image dataset. This was attributed to the fact that the trees were defoliating and the color of the leaves was turning brown, becoming difficult to distinguish. Even more challenging for the algorithm was the image dataset acquired in December, thus the results showed poor recognition accuracy (32.7%) (Table 1).

**Table 1. Accuracy of trees recognition using the developed methodology for images taken in May, November and December**

| Variables | Precision (%) |
|---|---|
| May | 100 |
| November | 85,7 |
| December | 32.7 |

The information of the trees position was sent to the UGV. To verify the produced results a pillion mission was conducted. In this mission the UGV was successfully navigated in the walnuts' orchard avoiding all the static obstacles.

## 5. Conclusions

The proposed approach consists a promising solution for real-time large-scale perceptional mapping of orchards physical environment. The main advantage of this work is the independence of the system from third-party and closed source software. Hence, the open source nature of the system provides easy deployment to various case studies. Another essential advantage of the proposed system is the ROS interaction of the autonomous vehicles (UAVs and UGVs).

The produced results confirmed the benefits of machine learning algorithm for image segmentation applications. The developed system was very accurate in recognizing the trees from images acquired when the trees canopy was developed. The accuracy dropped as the canopy was becoming difficult to distinguish at the stages after defoliation.

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