Individual Detection of Olive Trees Under Different Olive Planting Distributions

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***Abstract*—This work in progress addresses the challenge of individual detection of olive trees in different planting frames using advanced computer vision techniques and environmental analysis using point clouds. Accurate identification of individual trees is essential for efficient olive orchard management, especially in planting systems that vary in density, geometric layout and spacing between trees, aspects that strongly affect the way the field should be worked afterwards. Through the combination of image processing algorithms and geometric models, this study aims to develop a robust system that automates the identification of each tree, improving the monitoring of the crop and allowing for more accurate decision-making on the future treatment of each segmented entity in terms of health, maintenance, pruning. Preliminary results show the potential of these tools to optimize olive grove management in different planting configurations.**

Keywords-computer vision; plantation distribution; individual segmentation; point clouds.

I. Introduction

The digitization in agriculture is essential to improve the efficiency and sustainability of modern farming. In this context, image analysis using computer vision techniques and the application of algorithms based on spatial models plays an essential role in crop identification and monitoring, allowing applications such as disease detection, biomass calculation and optimization of agricultural resources once we are able to individualize each element of interest in the plantation.

In Spain, olive groves are one of the most representative crops. According to a 2019 report by the Undersecretariat of Agriculture, Fisheries and Food, the area occupied by olive groves in the Spanish territory amounts to 2,733,620 hectares, which represents 16.1% of the total cultivated area [1]. Moreover, Spain is the largest producer of olive oil in the world. Therefore, the possibility of individualizing the olive tree within a plantation is crucial for delimiting cultivated areas, making production estimates and improving soil and irrigation management.

Segmentation of olive groves from RGB (Red, Green, Blue) images presents several challenges. Factors such as variability in illumination, seasonal changes in vegetation, heterogeneity of terrain and its distribution, and the variability of ways to obtain the data make accurate tree identification difficult. Accurate detection and segmentation of olive trees are essential for monitoring crop health, optimizing resource allocation, and improving precision agriculture. Although traditional computer vision methods, such as segmentation algorithms in OpenCV, have been widely used, their effectiveness is often limited by environmental factors, such as variations in light, changes in foliage over the seasons, and terrain complexity. In contrast, deep learning-based methods, such as U-Net models and YOLO (You Only Look Once) architectures, have the ability to learn more robust features from large volumes of data, thus improving segmentation accuracy under changing conditions.

The purpose of this paper is to show the beginnings in addressing the challenge of individual olive tree identification in different planting distributions, using several advanced computer vision techniques as well as post-processing with spatial algorithms if necessary. Accurate identification of individual trees is crucial for efficient olive grove management, especially in planting systems that vary in density, geometric distribution, and spacing between trees. Through the combination of image processing algorithms and geometric models, this study seeks to develop a robust system that automates tree identification, improving crop monitoring and enabling more accurate decision making on the future treatment of each tree, in terms of health, maintenance, and pruning.

The remainder of the paper is organized as follows: Section II presents a review of existing related work, Section III describes the materials and methods used in the existing development to date, Section IV shows the results obtained, Section V discusses the results obtained, and finally, Section V provides conclusions and directions for future work.

II. Related work

The segmentation of vegetation in RGB imagery has been widely explored through both traditional computer vision techniques and more recent deep learning approaches [2][3]. Traditional methods have been extensively utilized due to their low computational cost and ease of implementation. However, with the rise of neural network-based models, these have become strong alternatives, offering superior performance under complex conditions [4] [5].

Among traditional approaches that do not require labeled datasets for training, the literature identifies three main strategies. The first strategy is based on color thresholds, where vegetation is segmented using predefined color value ranges, effectively differentiating vegetated areas from background elements. Another widely recognized methodology employs vegetation indices, which leverage combinations of spectral bands to enhance the detection of vegetation, such as the Normalized Difference Vegetation Index (NDVI) and other specialized indices [6]. The third strategy utilizes clustering methodologies, grouping pixels based on similar characteristics—such as color or intensity—to isolate regions corresponding to vegetation [7][8].

The advent of deep Convolutional Neural Networks (CNNs) has brought significant advances in segmentation tasks. These models are capable of learning complex hierarchical features from the images, achieving more robust and precise segmentations, particularly in heterogeneous environments [9].

In recent years, the integration of 3D modeling has further advanced vegetation segmentation, especially when combined with geometric and multisensor data. Unmanned Aerial Vehicle (UAV) platforms have proven highly effective for acquiring high-resolution spatial data, offering precise and real-time geometric information [10].

A particularly relevant development is the projection of RGB aerial imagery onto photogrammetric point clouds, enabling the alignment of 2D segmented regions with their corresponding 3D spatial structures. This projection process enhances the spatial understanding of vegetation and facilitates further geometric processing [11][12][13].

One of the main benefits of incorporating 3D analysis is the ability to filter out ground-level elements by applying relative height thresholds and techniques as voxelization [14] to split up the terrain or some algorithms based on regression [15] or Light Detection and Ranging (LiDAR) [16] techniques. This techniques are critical for isolating tree canopies from low vegetation and terrain noise, particularly in complex agricultural environments [17]. It is especially useful in olive groves, where understory vegetation can interfere with canopy-based measurements.

Additionally, the use of multisensor technologies—such as thermal, multispectral, and hyperspectral cameras—has enhanced the segmentation and mapping process [18][19] by providing a more comprehensive view of crop conditions. These sensors detect variations in reflectance that are not visible in the RGB spectrum, enabling differentiation between vegetation types and even revealing physiological traits that are useful for using traditional unsupervised algorithms for canopy segmentation [20]. The fusion of these multisensor datasets with advanced neural architectures (e.g., attention networks or 3D CNNs) [21] has helped overcome limitations of conventional methods by integrating spatial, spectral, and temporal information into more detailed and accurate segmentation outputs.

III. MATERIALS AND METHODS

This study presents a comprehensive methodology for the individual identification of olive trees under different plantation distributions, including traditional, intensive, and super-intensive scenarios, the difference between these types of scenarios lies in the proximity of the trees, as well as the fact that in intensive or super-intensive, the trees are planted in well-defined rows. To thoroughly validate the proposed approach under realistic agricultural conditions, various representative scenarios characterized by significant differences in spatial distribution, density, and morphological structure were selected. Figure 1 illustrates visual examples of each plantation type considered in this research.

The input data for the proposed methodology consist primarily of high-resolution (0.25m) RGB imagery captured by Unmanned Aerial Vehicles (UAVs). These UAVs are equipped

Figure 1. Comparison of olive orchard cultivation systems: (a) Traditional, (b) Intensive, and (c) Super-intensive.

with multiple sensor types, including multispectral, hyperspectral, and LiDAR sensors. The future integration of these multisensor data will enhance the comprehensive representation and characterization of the crops, significantly improving precision and reliability. Data acquisition was conducted through autonomous flight planning, achieving longitudinal and transversal overlaps exceeding 85%. Following data collection, precise three-dimensional models were reconstructed using Structure from Motion (SfM) photogrammetric techniques, resulting in detailed 3D point clouds with high spatial accuracy.

For the individual detection of olive trees within RGB images, a comparative study between previously trained neural networks and classical computer vision techniques was carried out (see Figure 2). It was observed that classical computer vision techniques offer greater efficiency and generalization across diverse plantation types, whereas neural networks required individual training tailored to each specific scenario. Therefore, classical computer vision techniques were ultimately selected for validating our proposal in the context of crop identification tasks.

Once individual trees are identified with the traditional image segmentation process within the RGB imagery, their labels are accurately projected into the three-dimensional point cloud space through a pinhole camera geometric model, represented mathematically by:

$$s \begin{bmatrix} u \ v \ 1 \end{bmatrix} = K[R \quad t] \begin{bmatrix} X \ Y \ Z \ 1 \end{bmatrix} \tag{1}$$

where ***u,v*** represent image coordinates, ***X, Y and Z*** denote 3D spatial coordinates, ***K*** is the intrinsic camera calibration matrix, ***R and t*** represents the rotation and translation matrices for extrinsic parameters, and ***s*** is a scaling factor.

Subsequently, a filtering stage was performed to exclude ground points, utilizing relative height analysis by defining a minimum height threshold as follows:

$$P_{filt} = p \in P \mid z(p) > h_{min} \tag{2}$$

where ***P*** represents the original point cloud dataset, and ***z*** indicates the relative height of each point concerning the terrain.

The outcome of this process is a precisely labeled 3D point cloud, clearly depicting the individual geometric structure of each olive tree. Currently, the methodology is being expanded through the development of an advanced clustering stage, applying algorithms such as Density-Based Spatial Clustering of Applications with Noise (DBSCAN) and Mean Shift. These clustering methods aim to achieve fully automated segmentation of each individual tree. The DBSCAN algorithm applied can be expressed in the following general form:

$$DBSCAN(P, \epsilon, MinPts) = C_1, C_2, \ldots, C_n \tag{3}$$

where $\boldsymbol{C}$ denotes the resulting individual clusters, ϵ defines the neighborhood radius threshold, and ***MinPts*** specifies the minimum number of points required to constitute a valid cluster.

Implementing this integrated methodological framework will significantly enhance the robustness, accuracy, and automation capability required for intelligent agricultural management of olive plantations, making it suitable for diverse real-world and commercial scenarios.

IV. Results

This section presents the detailed results obtained from applying various methodologies for identifying vegetation and olive trees across different plantation frameworks, as thoroughly described in Section III. The analysis includes a comprehensive comparative assessment between the segmentation methods employed, carefully examining the strengths and limitations of traditional techniques versus more contemporary neural network-based approaches. This comparison provides a rationale for the selection of traditional methodologies, highlighting their advantages in terms of simplicity, efficiency, and interpretability.

A. Image segmentation

Image segmentation was approached following three main approaches: traditional computer vision techniques and two deep learning models, namely U-Net and YOLOv8-seg. Both models were trained with datasets generated from the available images, representative of different planting configurations.

Since a dataset with validated manual segmentation (ground truth) was not available, the evaluation of the results was carried out by visual validation by experts.

As can be seen in the results shown (see Figure 2), in scenarios with clearly defined and well separated trees, such as in traditional plantations, neural network-based models provide a more accurate segmentation of the crowns. However, when working with denser and more complex configurations, such as in intensive and super-intensive frameworks, these models show difficulties in clearly distinguishing each individual tree. This limitation is mainly due to the fact that the models are at an early stage of training and have been trained with poorly generalizable datasets.

In contrast, the traditional computer vision approach, although less accurate in ideal cases, has shown greater consistency and generalizability in all scenarios, especially the more complex ones. However, its main limitation lies in the fact that it segments all visible vegetation, including grass or other non-relevant elements, without specifically differentiating tree canopies.

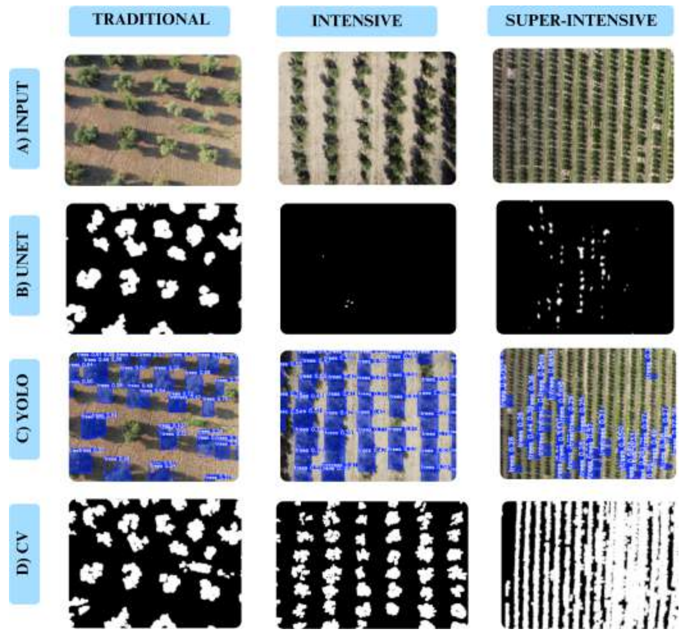

Figure 2. Olive tree segmentation process using the U-Net model(b), YOLOv8-seg architecture (c) and traditional computer visión techniques (d) on Input RGB aerial image (a).

In order to overcome this limitation, a post-processing based on three-dimensional terrain models is proposed, which allows discriminating low vegetation from tree canopy.

B. Geometrical post-processing

Once the most robust segmentation methodology had been selected, the binary masks generated on the RGB images were overlapped to obtain a clearer mask (Figure 3) and to be able to project onto the three-dimensional models of the environment, previously obtained by photogrammetry techniques like Structure from Motion (SfM) or by LiDAR scanning. This projection made it possible to visualize on the 3D model the initial result of the segmentation carried out on the RGB images.

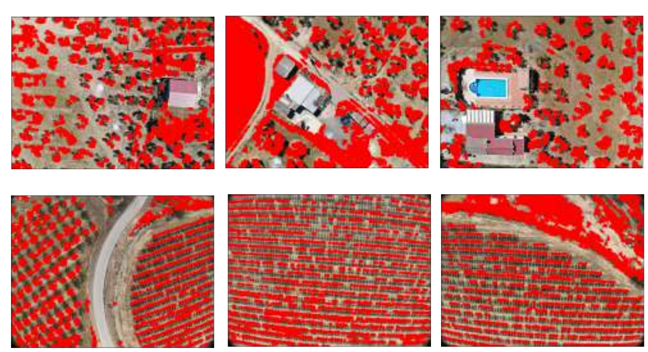

Figure 3. Example of overlay masks with their corresponding RGB image for segmentation with traditional computer vision methods.

At this stage, it was observed that many of the points identified as vegetation actually corresponded to low vegetation

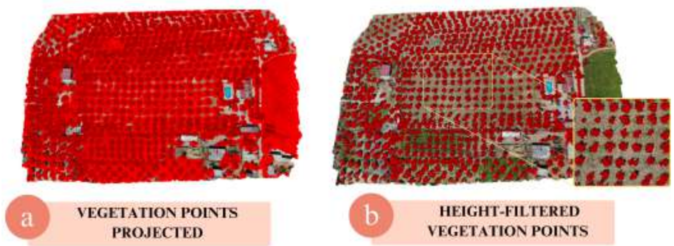

Figure 4. Comparison of point clouds: (a) vegetation points projected and (b) height-filtered vegetation points.

or ground elements, which generated noise in the representation of the tree canopy.

To solve this problem, geometric filtering was applied based on the relative height of the points, eliminating those whose elevation was below a defined minimum threshold with respect to the terrain. The result, shown in the Figure 4, shows a notable improvement in the cleanliness of the three-dimensional model, significantly reducing the number of unwanted points and retaining only those that represent the tops of the olive trees.

V. Conclusion and Future Work

This work presents the initial steps towards a robust methodology for individual olive tree identification across various planting designs. The aim is to spatially locate and monitor each tree entity using RGB drone imagery and 3D data representations.

A traditional image segmentation approach has proven to be effective and fast for isolating vegetation in various scenarios, demonstrating stability across all plantation types. Although preliminary experiments with neural networks such as U-Net and YOLOv8-seg show promising results, especially in simpler scenarios, their generalisability remains limited due to the early stage of training and the specificity of the datasets. Future refinement of these models is expected to improve their performance and potentially position them as the main segmentation tool for this project.

To complement image-based segmentation and to address problems such as interference from low vegetation, a 3D filtering methodology was applied. This process discards vegetation at ground level based on height thresholds, effectively isolating tree structures in the point cloud very quickly and successfully. However, current limitations include reduced robustness in terrain with significant topographic variation.

The current process allows us to segment vegetation with drones and isolate trees in 3D, laying the groundwork for clustering methods to identify individual olive trees. As future work, we plan to improve segmentation accuracy using advanced neural network models and develop a clustering mechanism capable of encapsulating individual trees with bounding boxes. This will allow the extraction of structural features and support precision agricultural applications such as tree health monitoring, pruning planning and yield estimation.

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