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Tree geometrical attributes measurement using UAV-born laser scanning

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Abstract

Forestry is the science and craft of creating, managing, using, conserving and repairing forests, woodlands, and associated resources for human and environmental benefits. Forest management as one of the categories of forestry, is essential to exploit forest's full economic and environmental value while ensuring the safety and resilience of the territory against natural or anthropogenic threats such as wildfires. UAV-based remote sensing is a powerful tool for forestry related tasks and measurements. Various studies and experiments have been conducted by different teams all around the world; proving the effectiveness and efficiency of this remote sensing platform and the machine learning techniques used for the analysis of the acquired data. In this study a multirotor UAV equipped with a LiDAR sensor payload is used to produce a high density point cloud of a forested area in Coimbra, Portugal. The acquired data is then used to produce point cloud-driven digital models for various forestry tasks including individual tree detection and total height. The calculated results are then validated by comparing them to the field data. The proposed methodology has potential applications for the detailed mapping of forest and wildland urban interface environments using autonomous, time and cost-effective means, towards proper forest land management for profitability and wildfire risk assessment.

1. Introduction

With the ever-increasing numbers of wildfires all over the world, as a result of human activity and climate change, now more than ever, forest management towards fire risk reduction has become a critical mission (Almeida et al., 2017), (Viegas et al., 2017). Deep knowledge about forest characteristics, more specifically vegetation parameters, is required for proper management. The trees' geometrical attributes are among the most important ones in terms of potential bio fuels for wildfires, as they govern the fire propagation through mechanisms such as crown and spot fires. Traditionally, fieldwork is required to obtain local vegetation and topography data. The extent and quality of the acquired data directly depends on the management and fire prevention plan for each municipality, and the experience of the landowner/service provider. It is also limited by its high logistic cost, in terms of time, money, and site access (Hernandez-Santin et al., 2019), often leading to insufficient or inadequate temporal and spatial data resolution.

Remote sensing, the process of obtaining information about an object or an area by measuring the radiation emitted by it from a distance (typically through airborne or spaceborne sensors), is a very useful technique to perform land mapping tasks and is a rapidly growing technology for forest monitoring (Adão et al., 2017; Müllerová et al., 2017; Nex & Remondino, 2014; Siebert & Teizer, 2014; Todoroff & Kemp, 2016). Many of these applications require individual tree detection (ITD), measuring their dimensions, state and assessing other relevant parameters.

Remote sensing can be divided into two general categories: data acquisition and data analysis. Data acquisition itself consists of two parts: remote sensing platforms (satellites, manned airplanes, high altitude balloons, unmanned aerial vehicles (UAVs) and terrestrial sensors) and sensor type. Satellites have allowed to monitor the entire world surface for different purposes (Tucker & Choudhury, 1987), (Tucker et al., 1984) and much of this data is freely available (www.copernicus.eu/en/access-data), but have coarse spatial and temporal resolutions. Aircraft systems offer increased spatial resolution, but at higher costs, often exceeding $20,000 per flight (Vandapel et al., 2004). Terrestrial delivery methods, such as handheld laser scanning devices or cameras mounted on tripods, offer high spatial resolution, but are limited in spatial extent and site accessibility.

With the need of a high spatial resolution and on-demand data, the use and development of UAVs have increased. Despite their shortcomings, which include low flight autonomy and payload capabilities, these platforms offer a complementary solution that is significantly better in terms of resolution and accuracy compared to satellites, costs less than aircraft systems and can be as precise as terrestrial delivery methods (Scholten et al., 2019). These set of advantages i.e., on demand data acquisition, high spatial and temporal resolution and relatively lower cost make UAVs very popular for forestry applications.

2. State of the art

Four types of sensors are commonly used with UAV platforms in Forestry applications; RGB cameras, Multispectral cameras, Hyperspectral cameras and LiDAR (Light Detection And Ranging) sensors. In case of the first three, the output is an image in the format of a multi-layered tensor, each layer representing a certain spectral band (3 for RGB, normally between 4 to 15 for multispectral and between 100 to 200 for hyperspectral). In case of laser scanners, the output is a point cloud; a set of data points in three-dimensional space that beside the cartesian coordinates each point can have various attributes that are built into the data structure (timestamps, labels, etc.). These datasets are pre-processed to perform various measurement, segmentation and classification tasks.

In the field of forest remote sensing, one of the most widely used models is the Canopy Height Model (CHM) (Gu et al., 2020; Ma et al., 2022; Miraki et al., 2021). This model consists of a digital surface constructed by rasterization of a point cloud set. First, the Digital Elevation Model (DEM) and Digital Terrain Model (DTM) are created; DEM and DTM are raster grids referenced to a vertical datum, DEM represents the whole scenery (ground and any observed object) while DTM only represents bare-ground; the subtraction of the two is the CHM (Figure 1). The CHM is the basis for various tree attributes measurements such as Diameter at Breast Height (DBH), Above Ground Biomass (AGB) (Wang et al., 2017) and Height Percentiles (Puliti et al., 2020).In this study a multirotor UAV platform equipped with a LiDAR payload is used to generate high density point cloud of a forested environment. This point cloud is then used to create DEM, DTM and CHM. Based on the CHM, ITD and individual tree height measurement tasks are done. The obtained data has multiple applications, including forest biomass monitoring and management for profitability and wildfire risk assessment.

3. Materials and Methods

3.1. Study area description

The study site is located in the city of Coimbra, Portugal. The area is at an elevation of 40 m above sea level, cantered at a western latitude of 40° 11' 05.8" and a northern longitude of -8° 24' 54.9" (see Figure). The climate is classified as Mediterranean climate according to Köppen climate classification (Beck et al., 2020). In the region, the dominant tree species are *Eucalyptus Globulus* and *Pinus Pinaster,* but the trees existing in the study site are *Olea europaea*. The study site is a flat ground with spaced trees and has an area of $4{,}900\ m^2$ which makes it ideal for validating the capability of the UAV payload for mapping trees.

3.2. Data Acquisition

3.2.1. Ground level measurements

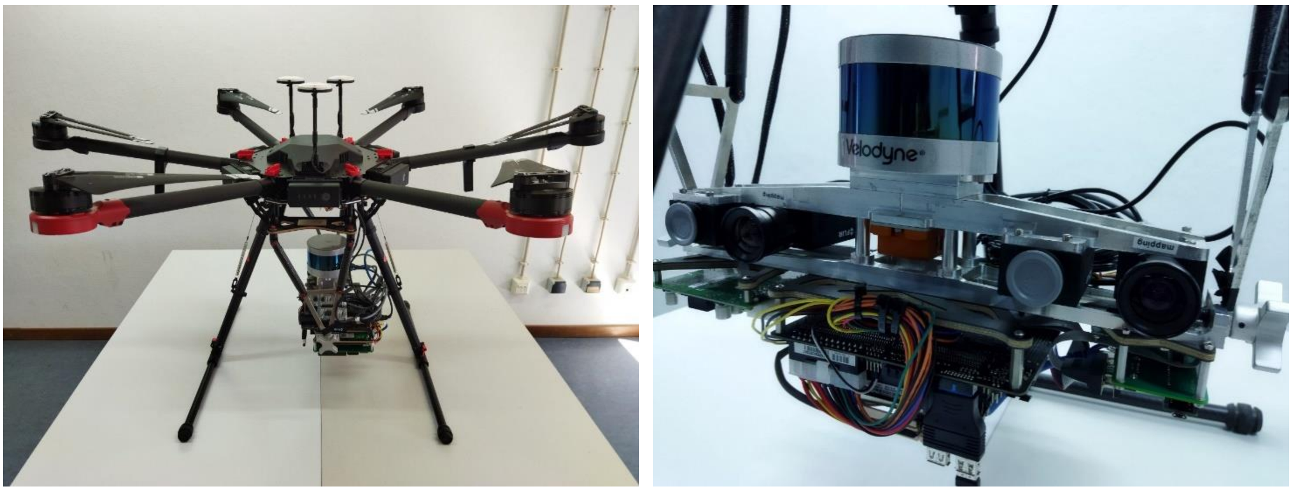
Manual ground level measurements were conducted to obtain the tree height and record their location with a GPS locator. A total of 8 randomly selected trees were measured using a *Nikon® Forestry Pro* hypsometer, to serve as the ground truth. This hypsometer has an accuracy of $\pm 0.3\ m$ for distance measurement and $0.1°$ for angle measurement when the target object's distance is shorter than 1,000 meters, therefore height measurement accuracy is $\pm 5.2 \times 10^{-4}\ m$ (www.nikon.com).

3.2.2. UAV Data Acquisition

The UAV platform used in this study is a DJI Matrice 600 pro, a Hexacopter UAV with the payload capacity of up to 6 kg. This battery powered UAV has a triple redundant positioning system which makes it ideal for topography and mapping applications. The flight took place in June 2022.

The LiDAR sensor payload used in the study is a multisensory payload developed at Carnegie Mellon University's Robotics Institute and consists of a LiDAR scanner (*Velodyne® Puck lite*, this scanner has 16 channels, vertical and horizontal field of view of 30° and 360° respectively and vertical and horizontal angular resolution of 2.0° and 0.1° – 0.4° respectively), an IMU unit (*XSENS® MTi-30, a 9 axis high performance IMU*), and a computer (CPU: *Intel® core™ i7 8th generation*, Motherboard: *Mini-ITX Gigabyte Z390 I Aorus Pro WiFi*, RAM:*16 GB DDR3*) that does onboard data processing, producing high density point clouds that are noise filtered and down-sampled. Figure shows the hardware that was used. The point cloud's mean surface density is 45 p/m^2.

Figure 1- Satellite image of the area (40° 11' 05.8", -8° 24' 54.9")



(a) (b)

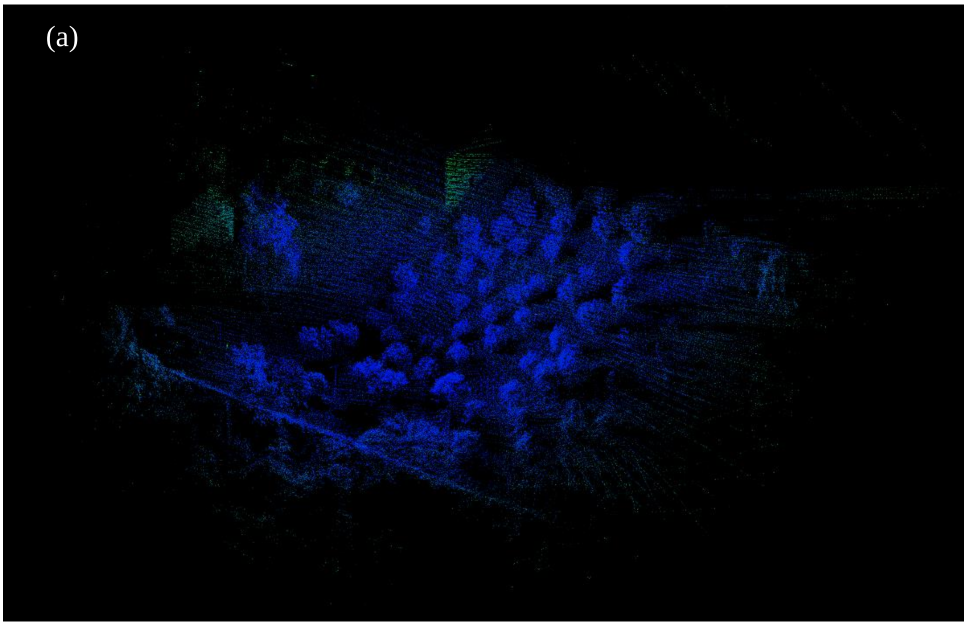
(c)

Figure 2- (a) Matrice 600 pro drone, (b) Sensor Payload, (c) Drone and the payload attached to it mid-operation

4. Results

4.1. Data pre-processing

The acquired point cloud map is shown in Figure . An open-source point cloud processing software (Cloud Compare, v 2.11.3) was used for point cloud filtering and rasterization.



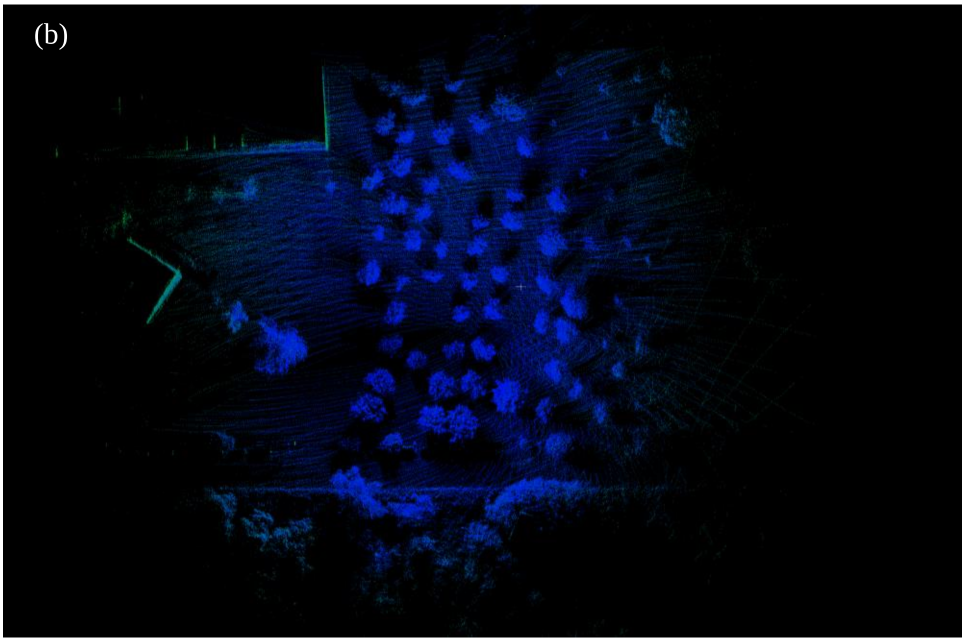


Figure 3 - Point cloud data of the study area (a) Isometric view and (b) Top view

First, the acquired point cloud map was pre-processed. The pre-processing included the following stages: 1- a noise filtering algorithm (Statistical Outlier Filter or SOR) was applied to the point cloud data to remove the points that were too far away from their neighboring point clusters. 2- After trimming the data to achieve the area of interest (AOI), a second filtering algorithm was applied on the data called Cloth Simulation Filter (CSF) to separate the ground points and above-ground points. This filter creates a mesh based on extrapolation of ground points to simulate the ground (see *Figure*). For more details about the algorithm please refer to (Zhang et al., 2016).

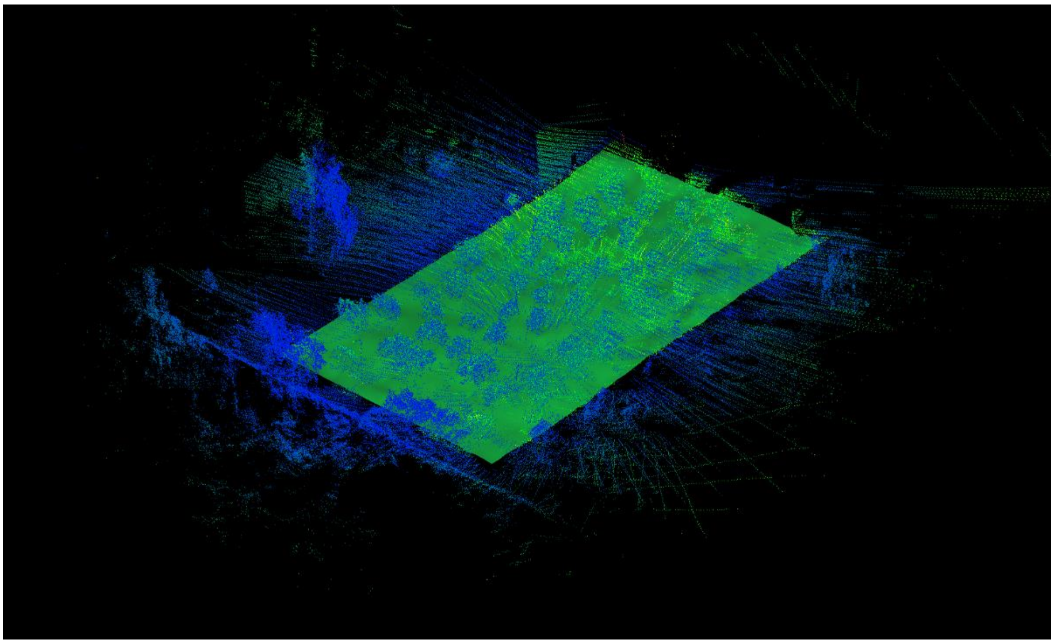


Figure 4- Generated mesh representing the ground, using CSF algorithm

The generated mesh serves as the simulation of the ground (DEM) and is used as the reference for measuring above ground points' elevation (*Figure*).

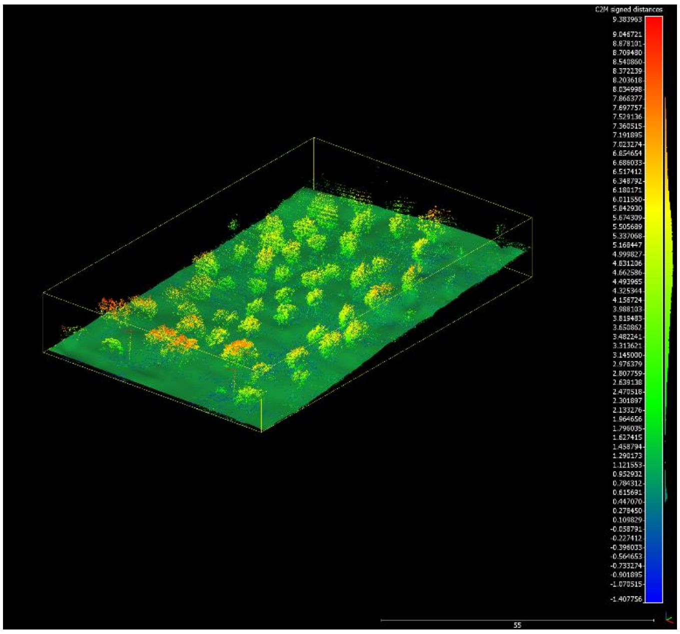


Figure 5- Pre-processed point cloud (colors indicate distance from ground)

4.2. Data Processing

After the above-ground points were annotated with their elevation relative to the ground, the point cloud was rasterized, resulting in the CHM of area (Figure).

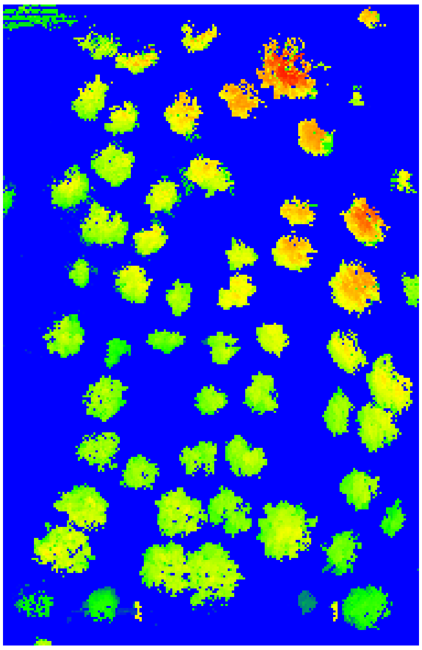


Figure 6- Canopy Height Model of the area

(R -v 4.2.0, 2021) was used for processing the CHM. To count the trees in CHM, a local maxima algorithm was used. The result is shown in Figure . Resulting height from this procedure is compared with the ground level measurements, obtained by the hypsometer, and shown in Table . The root mean square deviation (RMSD) from the height estimation is 0.11 m, demonstrating that this method is a viable solution to automatically measure tree geometrical attributes using UA 0V-born laser scanning.

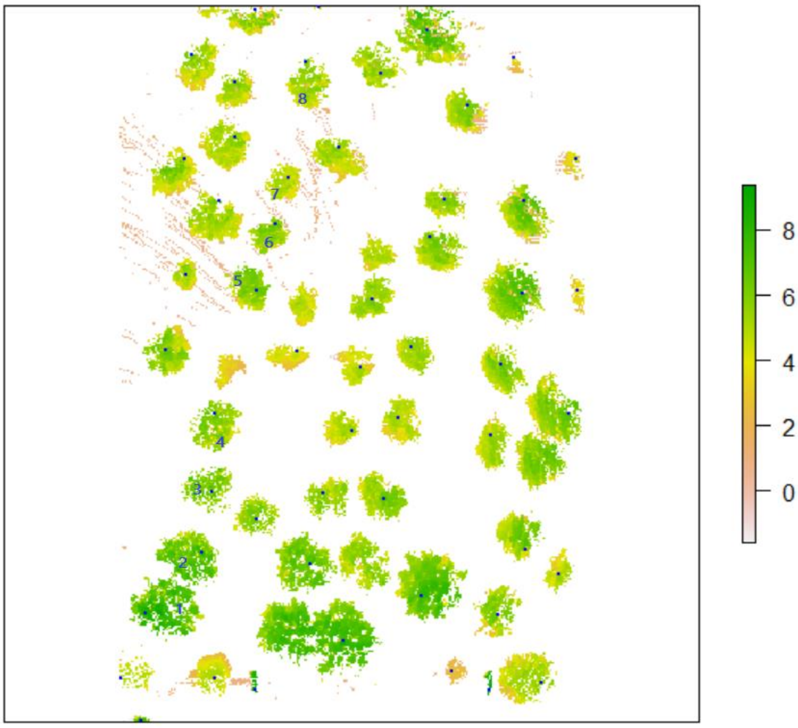


Figure 7- Tree Identification using local maxima filter

Table 1- Height measurement comparison

Tree Tag	Ground truth height (m)	Estimated height (m)
1	8.2	8.23
2	7.7	7.81
3	6.3	6.32
4	6.6	6.50
5	7.8	7.70
6	6.4	6.50
7	5.2	5.00
8	6.0	6.13
RMSD = 0.11 m		

5. Conclusion and Remarks

The comparison between the results from the UAV-born LiDAR scan processed data and the ground measurements reveal that UAV data is in good agreement with ground measurements, therefore the proposed system in this study can be used as a robust measurement tool for forestry applications. A few highlights of this study are listed as follows:

Down-sampling algorithm (point accumulation methodology) is a critical factor, density of point clusters has a direct effect on the quality of simulation of Object of Interest (OBI).

Flight and scanning scenario are the other deciding factors on the quality of obtained result. Depending on the defined task (specific forestry parameters to be measured), scan scenarios must be defined in terms of observed scenery, point density, energy and resources allocation.

The conducted flight and scan scenario is sufficient for an area with the similar characteristics as the one in this study. Denser and more complex environments require deeper and more complex scan scenarios.

A comparison between the manual field measurements time and drone flight is a good indicator of the efficiency of the proposed system; it took about 45 minutes to measure the heights of 8 trees (3 times each, for redundancy and error reduction), while the flying time was about 8 minutes (capturing more than 50 trees in the area, not to mention part of the scanned area was trimmed and ignored).

Manual measurement time per tree: 5.5 min

UAV-born measurement time per tree: 0.16 min

Therefore, the proposed system is more than 30 times faster than manual field measurement.

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