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Multi-beam LiDAR-derived data analysis for optimal canopy 3D monitoring in super-intensive almond (*Prunus dulcis*) orchards

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Abstract

Collecting 3D data from crops is becoming easier and more affordable with LiDAR-based technologies. The challenge is how to properly convert them into useful information to help farmers and advisors making better management decisions. Recent advances in LiDAR sensors allow users to get data not only in a single scanning plane, using a unique laser beam, but in several scanning planes using a number of simultaneous laser beams. Using multiple scanning planes provide different views of the scene at the same time and reduce hidden areas and shadows. In this study, an analysis of data obtained by a Velodyne VLP-16 LiDAR sensor was performed. The sensor uses 16 laser beams and was part of a mobile terrestrial laser scanner and was moved along super-intensive almond orchard alleyways to obtain a dense georeferenced 3D point cloud. The ability of different combinations of the 16 emitted laser beams in determining geometrical crop parameters was assessed. The parameters analysed were canopy height, width and cross-sectional area. Specifically, all three parameters were computed using a single central beam, a combination of the two outer beams and the use of all available 16 beams. The results showed that there were statistically significant differences in canopy width and cross-sectional area when using one, two or sixteen laser beams with different angles. The more laser beams considered, the larger the obtained canopy width and cross-sectional area parameters. Specifically, 28-33% larger width was obtained in comparison with the central beam and the cross-sectional area was doubled when all beams were taken into account. Canopy height estimations were less affected by the number of beams used. The increase of cross-sectional area was attributed to the ability of multi-beam combinations in obtaining more returns from inside the canopy together with the algorithm used which discards areas without returns within the cross-section. In conclusion, when using multi-beam LiDAR sensors, although they require higher storage and computing capabilities, canopies can be monitored with higher detail and more useful information can be extracted from each sensor reading.

Keywords: LiDAR, multi-beam, canopy geometry, orchards.

Introduction

Knowledge of canopy spatial variability across the field or orchard plays an important role in crop management. LiDAR (light detection and ranging) is a technology that can provide relevant information in this process (Escolà et al., 2017). For example, LiDAR allows some canopy geometric and structural parameters to be estimated with high accuracy (height, width, volume, leaf density and porosity). This enables the application of more sustainable management strategies, such as the site-specific application of plant protection products or the adjusting of fertirrigation rates, the monitoring of the vegetative growth, the ability to adapt the pruning intensity and/or the fruit detection for yield estimation, among other applications (Arnó et al., 2017; Colaço et al., 2018; Gené-Mola et al., 2020). In parallel, other works have recently investigated the quality of LiDAR multi-beam data in relation to GNSS (global navigation satellite system) absolute positioning of the sensor within the orchards, a scan matching approach was implemented and fused with the GNSS measurements, in order to decrease the localization error and improve LiDAR data consequently (Guevara et al., 2020).

These works represent significant advances in methodologies for using LiDAR sensing technology in agriculture, and in particular in 3D crops characterization. However, there is still a long way to go. For example, until now, most of the research in orchard characterization has been carried out with single beam LiDAR sensors, usually named as 2D LiDAR and with an instrument measurement accuracy around 3 mm (Auat Cheein et al., 2019; Siebers et al., 2018). However, recently multi-beam LiDAR sensors have appeared in the market, which allow 3D data to be acquired in different space planes at the same time. Using different scanning planes provide different views of the scene at the same time and reduce hidden areas and shadows. One example is the VLP-16 sensor (Velodyne, San José, California, USA), which emits 16 laser beams (905 nm wavelength). To the best of the authors' knowledge, there are very few works using multi-beam LiDAR sensors in crop characterization and none of them analyzes the improvement introduced by using more than one laser beam. Nevertheless, although several sensors can provide multi-beam scans, not always all of them are used to extract information from the object scanned and only one or two scanning planes or beams are used. One example using all the scanning planes is the work of Gené-Mola et al. (2019), in which a Velodyne VLP-16 was used for fruit detection in an apple orchard. For that purpose, a four-step fruit detection algorithm was developed using all the scanning planes allowing the localization of 87.5 % of the fruits.

Yuan et al. (2018) presented another work where all beams were used as a 3D scanning system for wheat height estimation. In that case, LiDAR provided the best results in comparison with ultrasounds. Specifically, they obtained an RMSE of only 0.05 m. In that study, the authors highlighted the advantage of stationary 3D LiDAR systems, whereas 2D LiDAR-based sensors required continuous motion to obtain 3D point clouds.

The objective of the present work is to assess the ability of different LiDAR single- and multi-beam combinations to determine basic canopy parameters like canopy height, width and cross-sectional area in a commercial super-intensive almond (*Prunus dulcis*) orchard.

Materials and methods

Study area

The study was conducted during the 2018 growing season in a super-intensive almond orchard (*Prunus dulcis* cv Lauranne avijor), grafted in a GF-677 rootstock (INRA), located at Alrasa commercial farm (Raimat, Lleida, Catalonia, Spain) (E 288330 m, N 4615874 m UTM 31T ETRS89). Three tree rows were scanned with a mobile terrestrial laser scanner (MTLS). A total of 255 m of tree row were scanned (85 m on each row). In that orchard, an experimental no pruning strategy was designed and, for that reason, the trees grew without limitations. The plantation has a pattern of 3.2 m between tree rows and 1.5 m between trees. On the other hand, tree rows form a continuous and vertical wall with branches growing from the tree row axis to all directions, even to the center of the alleyway. The orchard was planted during the winter of 2016/2017 and actually the production of almonds reached approximately 80% of full yield estimated for this kind of plantation.

LiDAR data acquisition and processing

A VLP-16 LiDAR sensor (Velodyne, San José, California, USA) was used as part of the self-developed MTLS. This sensor scans with 16 simultaneous laser beams with an angular range from 0º to 360º with an angular resolution of 0.2º. The different beams cover a field of view of 30º, that is they are 2º apart. When the sensor is mounted in a vertical plane perpendicular to the motion, the first beam is directed 15º frontwards and the last beam is redirected 15º backwards (Figure 1). The sensor can provide up to ~300,000 points s^{-1} and its location is georeferenced using a GNSS-RTK system, GPS 1200 (Leica, Wetzlar, Germany) with an absolute error of 0.01-0.02 m (horizontal/vertical).

To test the ability of different combinations of beams, only a portion of 10 m of a row was used. This portion accumulates a total of 4.2 million points, covering a little less than 7 whole trees. The sensor was mounted on a self-propelled mobile platform moving at a constant speed of 2 km h^{-1}. The scan process covered both sides of the crop to obtain a complete point cloud of the studied section (Figure 1). Although the LiDAR sensor can receive dual returns from each emitted beam, only the first return was used in this study.

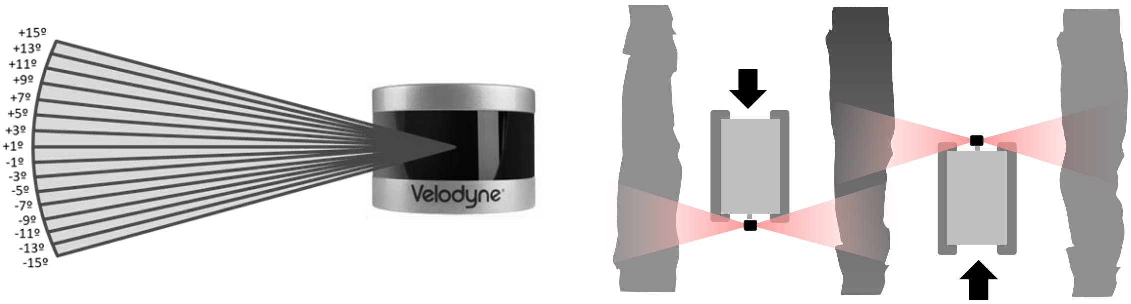

Figure 1. Left: top view of the LiDAR Velodyne VLP-16 sensor used in the trials mounted on a vertical plane. Lines represent the 16 laser beams emitted by the sensor. Angle and sign are shown for each beam. Right: top view of the field procedure to scan the 10 m-long tree row section with the MTLS.

The LiDAR-derived point cloud was created using MATLAB® (R2018a, Math Works Inc., Natick, Massachusetts, USA), running a self-developed code that is publicly available on the GITHUB platform (https://github.com/GRAP-UdL-AT/MTLS_point_cloud_generation). The point cloud was processed with RStudio (Version 1.2.5001 using R version 3.6.1 as calculation engine). For that, an adaptation of the self-developed R code described in Llorens et al. (2019) was used. By applying this code, geometric parameters of the canopy were extracted every 0.1 m along the studied portion of row. For this test, three basic geometric parameters were studied: canopy height, canopy width and canopy cross-sectional area. Canopy height corresponds to the maximum height of the vegetation row every 0.1 m in the analysis area of 10m-long. Canopy width was calculated as the average of the maximum widths in vertical increments of 0.1 m every 0.1 m along the analyzed section (Figure 2a). The cross-sectional area was calculated by projecting each 0.1 m-long section onto a vertical plane perpendicular to the row longitudinal axis and overlapping a 0.05 m x 0.05 m regular grid. Only the area (0.0025 m^2) of those cells containing points was considered to compute the total cross-sectional area, in a sort of an occupancy grid (Figure 2b). The size of the grid was chosen to be similar to the average size of the almond tree leaves. This procedure was applied to point clouds obtained from three different beam combinations: the first combination used only one of the central beams (beam -1º), the second combination used the two outer beams (+15º and -º15º) and the last combination used all beams (Figure 1).

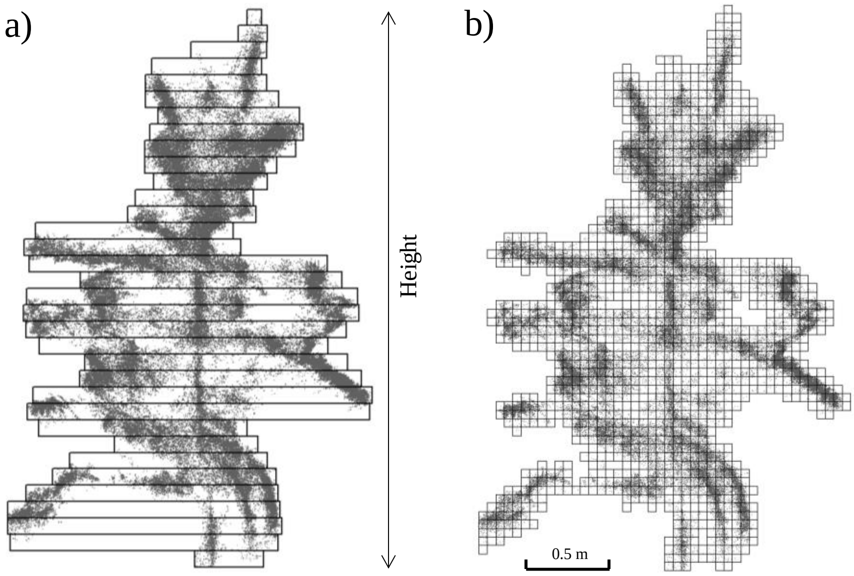

Figure 2. Graphical representation of a cross-section point cloud of section projected onto a vertical plane perpendicular to the tree row axis showing the procedure to calculate the geometric canopy parameters. a) Maximum height of the canopy and calculation of the canopy width along 0.1 m vertical increments. b) Determination of the cross-sectional area with a sort of an occupancy grid (0.05 m x 0.05 m). For better visual understanding, points of a 0.25 m-long row section are represented.

Statistical analysis

With the processing of geometric parameters, a value every 0.1 m along the row was obtained for each parameter and for each beam combination That means 3 samples of 100 observations for each canopy parameter to be compared. For the comparison, a mixed model ANOVA was used. Instead of using a one-way model with only one factor, it was decided to use a mixed model with a fixed factor (LiDAR beam combination) and a randomized factor (tree position within the row) to prevent having too much experimental error and to increase the ability to find significant differences. The model (1) is described as follows:

$$y_{ij} = \mu + \alpha_i + B_j + e_{ij} \tag{1}$$

where y_{ij} is the value of each geometric parameter calculated using the combination of beams i for a particular row location j, μ is the mean value of the sample, α_i is the effect of the beam combination (fixed effect), B_j is the random effect of row location, and e_{ij}

accounts for the residual component. To apply this model, a random sample of 10 points was selected within the experimental tree row. The sample locations were used for all the analysed crop parameters. Statistical analysis was performed using the statistical software R (R Development Core Team, 2013) under an RSTUDIO environment (ver. 1.2.3001). Tukey's HSD (honestly significant difference) test was used for multiple comparisons and the significance level was set to $\alpha = 0.05$.

Results and discussion

Figure 3 represents the differences between point cloud densities of a 0.25 m-long section depending on what combination of beams was used. Although the figure represents 2.5 times more points than the points that would be represented if only 0.1 m of the row were graphed (done for better visual observation), it is easy to see the differences in the amount of points and the information obtained when more laser beams are collecting data. If more beams are working, more detailed information can be captured from the crop because each beam is scanning the object from a different angle. For this reason, more detail of the internal parts of the canopy can be obtained when all beams are used.

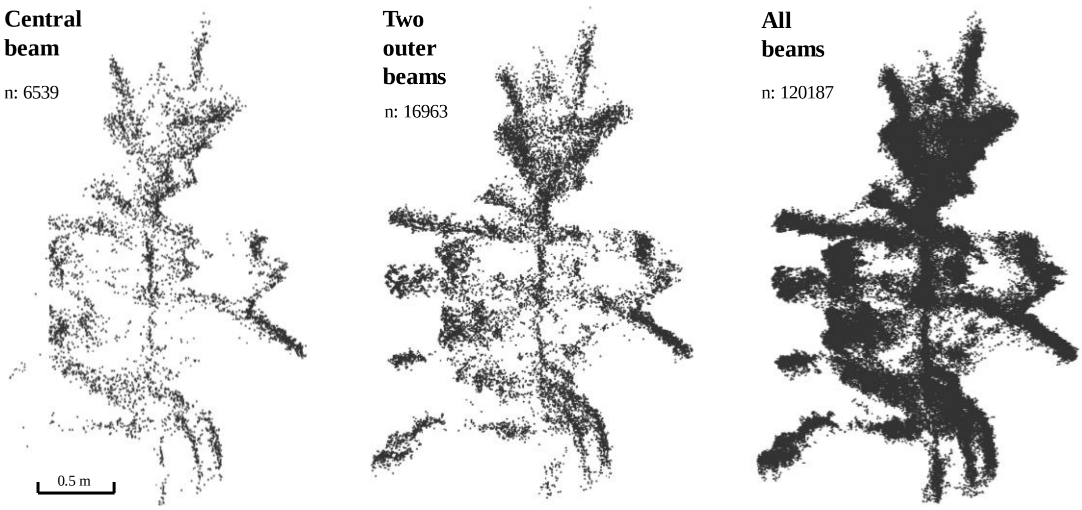

Figure 3. LiDAR point cloud of a 0.25 m-long row section for each combination of beams. The number of points (n) is provided. For better visual understanding, points of a 0.25 m-long row section are represented.

Mean values for each crop parameter are shown in Table 1. No big differences were found between the average of the sampled points (N=10) and the average of all the samples in the 10 m-long row (N=100) in canopy width and cross-sectional area. Larger differences can be found in canopy height caused by the random sampling process. Canopy height estimation was less affected by the combination of beams used, in this case absolute differences smaller than 0.15 m were found. However, width and cross-sectional area were highly affected by the beam configuration, high values were obtained when all beams were used. Specifically, 28-33% larger width was obtained in comparison with the central beam and the cross-sectional area was doubled when all beams were taken into account. These differences would occur in the case a single beam sensor or 2D LiDAR (like Hokuyo or SICK models) were used, because this kind of sensor uses only a single laser beam such as the central beam in VLP-16. When the two outer beams are used, the obtained cross-sectional area is about 25% smaller than the area obtained when all beams are considered.

Table 1. Results of the mixed model ANOVA and mean comparison for the different crop parameters and beam combinations (N=10). Values in columns with the same letter are not significantly different (p<0.05). Values in brackets are the mean of all measurements in the 10 m-long section (N=100).

Beam combination	Height (m)	Width (m)	Cross-sectional area (m^2)
Central beam	2.924 b (*2.598*)	0.726 c (*0.770*)	1.063 c (*0.948*)
Two outer beams	2.959 ab (*2.655*)	0.870 b (*0.903*)	1.454 b (*1.323*)
All beams	3.052 a (*2.777*)	0.962 a (*0.983*)	2.077 a (*1.868*)

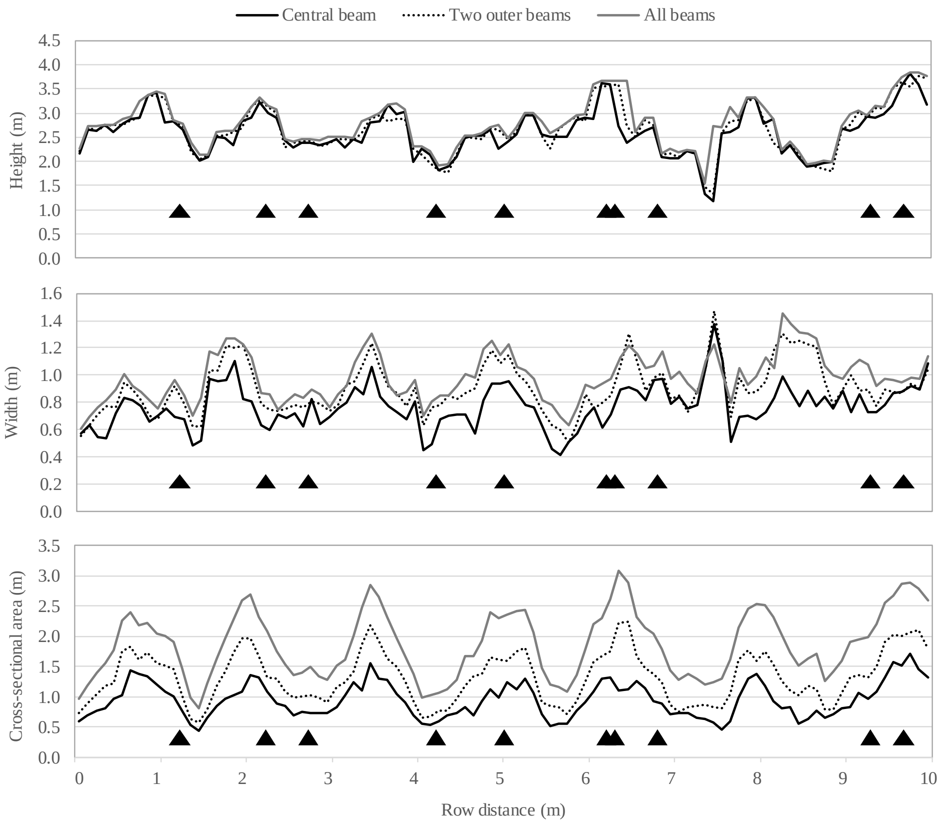

Figure 4. Values obtained for each parameter along the 10 m-long row section every 0.1 m. Black triangles indicate the location of the sampling point on which the mixed model was applied.

It is interesting to see the evolution of each parameter along the crop row as shown in Figure 4. This figure shows all 100 readings along the 10 m row length and covers a stretch of almost 7 almond trees. The graphs show the differences detected in the statistical analysis. In the case of canopy height, the lines follow almost an identical trend. In the case of canopy width, there is a similarity between the use of two outer beams and all beams. The use of only a central beam results in clearly lower values and, therefore, in underestimating the canopy width.

In the case of the cross-sectional area parameter, the differences are evident, and no overlapping lines appear in all the range. Despite being a none-pruned canopy, the cross-sectional area is the only one of the three parameters that allows the position of each tree trunk in the row to be detected. This individualization of trees appears in each combination of beams but it is less evident when only one beam is used.

In Gené-Mola et al. (2020) a multi-beam LiDAR sensor was used. In that case the main objective was to detect apples to study the productive performance of the crop, but at the same time geometric characteristics of the vegetation were determined. For this task, the authors used all the beams of the sensor and determined the same geometric parameters that have been analyzed in the present work: canopy height, width and cross-sectional area. To determine height and width the authors used the same procedure. But in the case of cross-sectional area, the computing method differs because it was calculated from the maximum width at each of the measured heights (Figure 2a, every 0.1 m in height). Therefore, it is possible that the fact of not taking into account the internal gaps of the vegetation, the section values would have been different and no differences would be detected between the trunk area and the area between trunks, a fact that is detected in the method presented in this article even when not using all sensor beams.

As the developed methodology is only taking into account geometric parameters of the canopy, the current study could be extrapolated to other perennial crops with similar training systems, that is non isolated tree row crops with relatively narrow canopies.

For the current work, after analyzing the results, the all-beam configuration would be the most recommended setting for an accurate characterization of the vegetation. However, this configuration is the one requiring more storage and computing capabilities. As an alternative, an analysis using the two outer beams or only the central beam would be less storage and computing demanding and would be enough to determine the spatial variability of a plot. Nevertheless, any of the laser beam combinations could be used to design site-specific operations or to guide the farmer for a stratification of sampling points in order to do an analysis at the productive level. A tool for quantifying the spatial variability is very important for improving management decisions and agricultural practices (Arnó et al., 2017).

To the best of the authors' knowledge, the present work is the first to expose a comparison of results obtained using different combinations of laser beams obtained with a multi-beam sensor. In future works, the correlation between the different laser beam combinations should be determined as this could optimize the analysis processes when large amounts of data are to be processed. As an example, processing a point cloud from only 2 beams (point cloud of 0.5 million of points for 10 m of row) represents a significant reduction in processing time in relation to the process of a point cloud with all beams (4.2 million of points in the same 10 m). In terms of amount of data, it represents more than 8 times more data.

Conclusions

The present study has focused on evaluating the effect of using different laser beam combinations to extract geometric information from perennial tree crops. Important differences were found when canopy width and cross-sectional area parameters were extracted. Those differences need to be taken into account when different LiDAR sensors are used to obtain the same parameters, or if a specific parameter needs to be measured with different sensor configurations. In conclusion, the use of multi-beam LiDAR sensors allows canopies to be characterized and monitored with higher detail due to the extra points of view offered by the different laser beams.

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