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Assessment of measurement uncertainty when using 2D mobile laser scanner to estimate tree parameters

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Accurate estimation of geometrical parameters of horticultural plantations is essential for precise management. Tractor mounted 2D mobile LiDAR systems may allow for measuring the growth of fruit trees in the future. Though the method has some specific benefits such as an active light source for measuring in varying lighting conditions, it can, however, generate biased dataset due to perturbating influence of range and incidence angle of the laser beam. To quantify these effects, a box-shaped object with known dimensions was utilized in this study. The surface of the metal box was modified with barium sulphate as diffusive coating. Results point out that the estimated mean height of the box was found smaller than actual height, while width estimation was overestimating actual width. Highest root-mean-square error (RMSE) was 2.09% and 0.91% for height and width estimation, respectively. It was found that the estimation of the volume of the box, and subsequently of the fruit tree, using segmented convex hull algorithm was feasible for measuring the canopy volume in a commercial fruit tree plantation.

Keywords
LiDAR calibration, measuring uncertainty, registered point cloud, tree volume

In precision horticulture, the application of light detection and ranging (LiDAR) sensors appears as an emerging technique for plant-individual data acquisition. The reason for the popularization of this technique in the horticultural community is its ability to produce three-dimensional (3D) data in high spatial resolution in the form of point cloud within a short acquisition time. Furthermore, the LiDAR laser scanner works with an active light source providing some resilience against changing incidence lighting condition. Reconstructed 3D tree structure from mobile LiDAR point cloud contains information on the tree geometric parameters such as tree height, width, volume, stem & branch diameter, stem position, leaf area and leaf area density (Oveland et al. 2017, Rosell et al. 2009). As a drawback, the plant phenological parameters derived from point cloud are often biased due to vegetation occlusion (Pimont et al. 2018) and leaf orientation angle.

Utilization of mobile two dimensional (2D) mobile LiDAR sensors in horticultural applications has a number of benefits compared to terrestrial 3D LiDAR systems (TLS) and airborne LiDAR systems (ALS): It can operate in between the tree rows to produce the georeferenced 3D point cloud in the form of cross-sections of the object tree. Furthermore, it is a fast and cost-effective technique to obtain real-time, high spatial and temporal resolution data (Palacin et al. 2007). Various approaches have been applied to estimate the canopy structural and geometrical information (tree height, stem diameter etc.) from the point cloud (Jimenez-Berni et al. 2018, Oveland et al. 2017). Furthermore, statistical

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regression analysis and prediction models derived from LiDAR metrics and reference readings are utilized to extract leaf area, canopy volume, and light attenuation (Herrero-Huerta et al. 2018, Wu et al. 2018). However, results of LiDAR-derived tree parameters are directly influenced by the quality of the point cloud. LiDAR accuracy is the deviation of the estimated value from the true value of the object.

The specific objectives of this study were: (i) to assess the measuring uncertainty of the mobile LiDAR scanning system, measuring a simple geometric structure such as a box, (ii) to estimate the object volume from box and tree point cloud data. The results of this study will help to understand the capability of the mobile LiDAR scanning system, when utilized in the orchard to estimate tree parameters.

Material and Methods

Description of the LiDAR Scanning System and LiDAR Data Pre-processing

In this study, a 2D LiDAR sensor (LMS511 pro model, Sick, Düsseldorf, Germany) was used. This laser scanner operates based on the time of flight (TOF) technique. The distance from the sensor to object is determined from the total travel time of a single laser pulse from the source to object and back to the receiver at the velocity of light. To determine the total travel period, the time of pulse emission t_e and of pulse reception t_r is recorded and the time difference considering the same pulse ($dt = t_r - t_e$) is calculated. Subsequently, the distance ρ to a surface is computed (Equation 1) according to the speed of light c.

$$\rho = c\,\frac{dt}{2} \qquad \text{(Eq. 1)}$$

The LiDAR system was mounted on an agricultural tractor unit with an adjustable rigid aluminium frame carrying the laser scanner, inertial measurement unit (IMU) (MTi-G-710, XSENS, Enschede, Netherlands) and rover antenna of real-time kinematic global navigation satellite system (RTK-GNSS). The IMU provided role, pitch, and yaw information at a frequency of 400 Hz as the tractor orientation changes due to its movement. In this study, the laser scanner was set with angular resolution of 0.1667°, scanning frequency of 25 Hz, scanning angle of 190°, and scanning range of 80 m. The RTK-GNSS (AgGPS 542, Trimble, Sunnyvale, USA) was used to georeference each scan of the laser scanner providing real-time position at 450 Hz frequency. The RTK-GNSS has horizontal and vertical accuracy of ± 25 mm + 2 ppm and ± 37 mm + 2 ppm, respectively. With a distance of 0.24 m from the laser scanner, the IMU was attached providing an accuracy of 1.0° root mean square error (RMSE) for the heading in static and dynamic mode, and 0.25° RMSE and 1.0° RMSE for both pitch and roll in static and dynamic mode, respectively.

All the sensors were connected to an on-board laptop computer, in which a data acquisition program was installed. The program was developed in Visual Studio (Microsoft, USA) in order to record the multi-sensor raw data in separate text files along with timestamp. A python (version 3.6, Python Software Foundation, https://www.python.org) script was written to pre-process and interpolate the IMU and RTK-GNSS datasets to LiDAR laser scanner frequency using cubic spline interpolation. Thus, the multi-sensor raw datasets were synchronized with same timestamp. The LiDAR data were filtered by applying a distance threshold between 0.05 m and 4.00 m from the sensor. Coordinate transformation, rotation and translation was applied and, subsequently, point cloud registration, removal of ground points and iterative closest point algorithm (ICP) to stich the point cloud pair was carried out according to the methodology described by Tsoulias et al. (2019).

Data Acquisition

Scanning of a box from all four sides with the LiDAR was performed in outdoor condition. The aluminium box of 2.0 × 0.15 × 0.15 m width was used as a standard 3D object for calibration experiment (Figure 1a). The thickness of the box wall was 2 mm and the box acted like a solid rigid object showing no geometrical deformation. In general, smooth metallic surface shows specular reflection properties for any source of incident light. For the LiDAR scanning, it was anticipated that striking laser beams with high incident angles might not return to receiver resulting in missing points within the point cloud. To mitigate this effect, the box was coated with barium sulphate ($BaSO4$) to create diffusive reflecting surface, which maximized the chance of return all laser hits for all incident angles. The distance between the center of laser scanner and box was maintained at 2 m. The laser scanner was kept at a height of 1.2 m above the ground surface (Figure 1b). Three LiDAR scans were done for each side of the standard box.

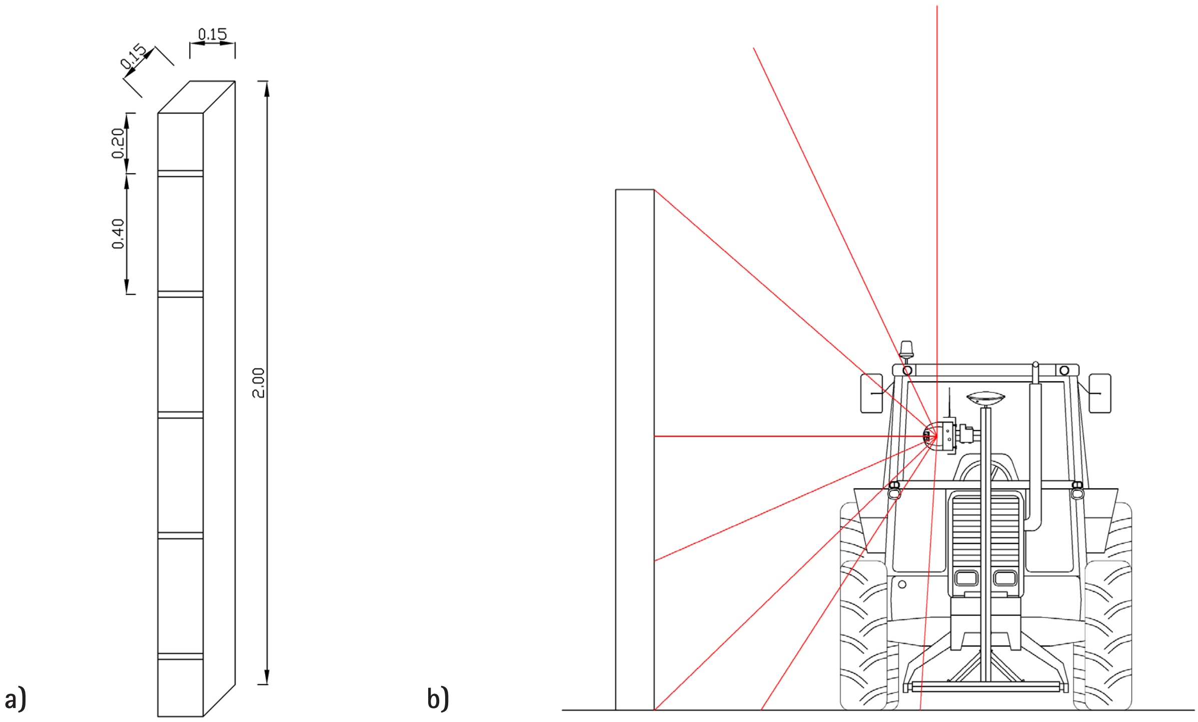

Figure 1: (a) Aluminium box coated with barium sulphate ($BaSO4$) with dimensions provided in m, (b) Schematic diagram of box measuring process with tractor mounted mobile 2D LiDAR system

Apple trees (n = 150) were scanned in a commercial orchard located in Markendorf, Frankfurt (Oder), Germany in 2018 (Latitude 52.313° N, Longitude 14.476° E). Due to late frost, no fruit was present at the trees. A tractor was used as a platform, carrying the scanning system in a side view of the trees. All the trees of a row were scanned from two opposite sides to obtain the complete 3D dataset and also to minimize the occlusion effect on the point cloud. The mounting height of the laser scanner was determined at half the maximum height of the object. Few trees were selected arbitrarily for collection of the reference data (n = 3): height and width at 6 heights. For scanning the box and trees, the tractor along with mounted LiDAR system was driven at an average forward speed of 0.5 km h^{-1}.

Point Cloud Analysis and Uncertainty Determination

Point clouds of the four sides of the box were generated from the LiDAR scan data and analysed individually for estimating geometrical dimensions (height and width). Open licenced python environment (version 3.6, Python Software Foundation, https://www.python.org) and CloudCompare®, an open-source software (version 2.10, Telecom ParisTech, France; http://www.cloudcompare.org/) were utilized for analysing and visualization of the point cloud, respectively. Each side's point cloud was cleaned and denoised by removing outliers using statistical outlier removal (SOR) algorithm. Since the surfaces of the box were coated with highly diffusive material, all laser hits on its surfaces returned to the LiDAR's receiver. An algorithm was written to analyse the surface point clouds by means of extracting vertical slices of 1 cm, and the mean distance between top and bottom was calculated by subtracting the maximum and minimum coordinates in the z axis. Similarly, the width of each side of the box surface was calculated by slicing the point clouds horizontally in sections of 1 cm subtracting the maximum and minimum coordinates in the y axis. The estimated height and width were compared to the known dimension of the four sides of the standard box.

The reconstructed 3D box point cloud was used to determine uncertainty with respect to volume estimation. The volume of the 3D object was estimated from the point cloud using segmented convex hull approach (Auat Cheein et al. 2015), applied along the vertical profile for both box and tree point clouds. According to Auat Cheein (2014), subsetting of entire dataset and applying the convex hull algorithm on each subset does not compromise result for determination of convex hull of the total dataset. Moreover, segmentation significantly reduced the computational costs and memory usage. In this study, the segment height was determined at approximately one-tenth of the average scanned object height. Therefore, 0.20 m and 0.30 m segment heights were applied for box and tree point cloud, respectively, and total volume was estimated by adding all volumes obtained from segments. The LiDAR estimates of box and tree volumes were compared with manually measured reference volumes.

The deviation of LiDAR estimated values from the actual values was used to calculate the mean bias error (MBE), mean absolute error (MAE), root mean square error (RMSE) and standard deviation (SD) (Equations 2–5).

$$\text{MBE} = \frac{1}{n}\sum_{i=1}^{n}(d_{r,i} - d_{lidar,i}) \quad \text{(Eq. 2)}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|d_{r,i} - d_{lidar,i}\right| \quad \text{(Eq. 3)}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(d_{lidar,i} - d_{r,i})^2}{n}} \quad \text{(Eq. 4)}$$

$$\text{SD} = \frac{1}{n-1}\sqrt{\sum_{i=1}^{n}(d_{lidar,i} - d_{mean})^2} \quad \text{(Eq. 5)}$$

where, $d_{r,i}$ is the reference value of the metal box, $d_{lidar,i}$ is the dimension of the box estimated by the LiDAR for time instance i, d_{mean} is the mean dimension estimated by LiDAR and n is the number of the measured points for each profile.

Results and Discussion

Estimating Geometrical Parameters from Box Point Cloud

The average spatial resolution was found 1.7 points per square cm where average 16 vertical scan slices were observed in the point cloud of box sides. Estimated height of the box ranged from 1.78 m to 2.02 m (Table 1). Mean estimated height (1.96 m) was found slightly below the actual height (2 m). Height estimation uncertainty in terms of MBE, MAE and RMSE % were 3.95 mm, 5.03 mm and 2.09 %, respectively. Similarly for width estimation, mean width (0.16 m) was found enhanced compared to the actual width of the box (0.15 m) and the estimated width of vertical sections along the heights ranged from 0.14 m to 0.17 m. The RMSE of width estimation was found at 0.91 % (Table 1).

Table 1: Estimation results of height, width from box point cloud and its statistical analysis in terms of mean bias error (MBE), mean absolute error (MAE), root mean square error (RMSE) and standard deviation (SD).

Measurement	Min (m)	Max (m)	Mean (m)	MBE (mm)	MAE (mm)	RMSE (%)	SD (mm)
Height	1.78	2.02	1.96	3.95	5.03	2.09	74.67
Width	0.14	0.17	0.16	-0.61	0.83	0.91	8.04

To estimate the box volume from the reconstructed box point cloud (Figure 2a), the entire point cloud was segmented horizontally. Points belonging to every segment of 0.20 m height were extracted and convex hull was calculated (Figure 2b).

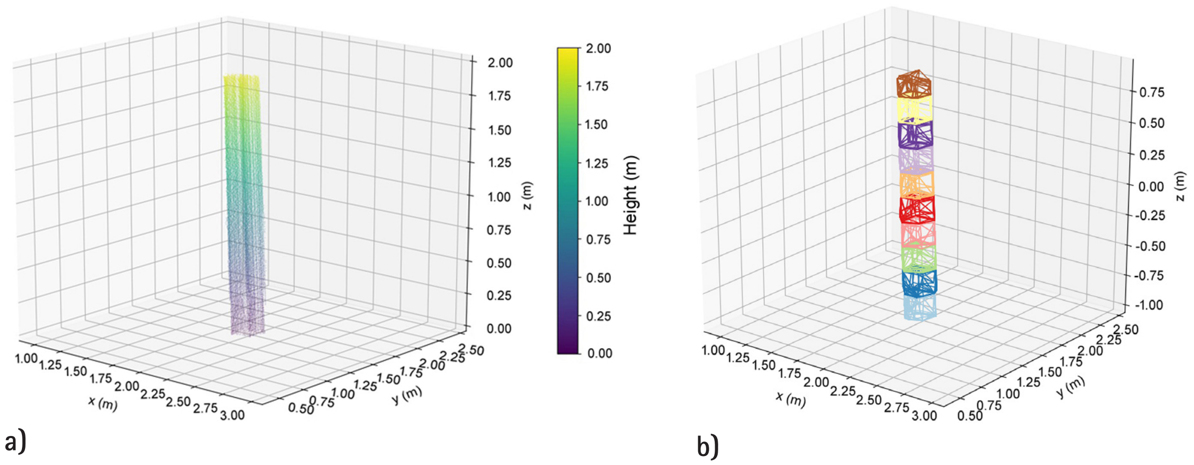

Figure 2: (a) Reconstructed 3D point cloud of the coated metal box. (b) Visualization of segmented convex hull approach applied on box point cloud with segment height of 0.20 m marked in false colour.

The volume associated to the sum of segments was calculated (Table 2). To verify the measuring uncertainty of volume estimation of each segment, MBE, MAE, and RMSE were calculated. The ranges of MBE, MAE and RMSE were −0.25 to −0.82 dm^3, 0.25 to 0.82 dm^3, and 0.253 to 0.822 dm^3, respectively. It was pointed out that the volume of all segments was overestimated. It was also seen that comparatively lower values were estimated for top and bottom segments. This may be due to lost points, while removing the ground surface from bottom segment and while filtering outliers.

Table 2: Box volume estimated by means of LiDAR (Vlidar) and statistical errors along the vertical profile of the metal box (no. of scan, n = 3) with equal volume of 4.5 dm^3 for each segment.

Segments position	**Vlidar (dm^3)**	**MBE (dm^3)**	**MAE (dm^3)**	**RMSE (dm^3)**
Seg1 (0 to 0.2 m)	4.8	-0.26	0.25	0.258
Seg2 (0.2 to 0.4 m)	5.1	-0.51	0.50	0.506
Seg3 (0.4 to 0.6 m)	5.3	-0.77	0.76	0.767
Seg4 (0.6 to 0.8 m)	5.3	-0.82	0.82	0.822
Seg5 (0.8 to 1.0 m)	5.3	-0.77	0.76	0.768
Seg6 (1.0 to 1.2 m)	5.1	-0.57	0.57	0.573
Seg7 (1.2 to 1.4 m)	5.2	-0.70	0.69	0.700
Seg8 (1.4 to 1.6 m)	5.2	-0.72	0.71	0.717
Seg9 (1.6 to 1.8 m)	5.2	-0.73	0.73	0.731
Seg10 (1.8 to 2.0 m)	4.8	-0.25	0.25	0.253

Analysing the height estimation resulted in bias and diffusion error below 1 cm. Width estimation results showed slightly reduced measuring uncertainty. Earlier works reported mean absolute error of 8.18 mm with a bias of 2.75 mm, particularly with enhanced incident angle. This was explained by spikes and attenuation due to scattering at the edges of the object (Tsoulias et al., 2019). These causes may have been reduced in the present study by the diffusive coating. Results of volume estimation also revealed that the volume calculated by means of segmented convex hull changed along with the height of the object. The estimated volume might vary due to distance from the scanner and incident angle of the laser hits on the box. As the LiDAR scanner was set at 1.2 m height, the points of the nearest box segment (Seg6) had the lowest incident angles. The enhanced diameter of the laser beam in lower and higher segments hit partially at the edges of the box, which caused a dislocation of the edge points. As a result, larger volume estimates may occur.

Estimation of Tree Volume

The total tree volume was estimated utilizing a segmented convex hull approach, when analysing the tree point cloud (Figure 3). Manually measured reference volumes of tree sections were plotted against LiDAR-derived corresponding segments (Figure 4). The result showed a good agreement for the coefficient of determination (R^2 = 0.75). As the convex hull approach finds the outer points that contained all the points, overestimation of tree volume occurs due to irregular shape of trees. For example, at the top segment of the tree where many new branches are growing with small, immature leaves, the volume has a high porosity and should be low. However, the estimates using convex hull resulted in a larger volume compared to the actual volume. A better representation of the tree reconstruction was achieved in the middle and lower sections of the fruit trees.

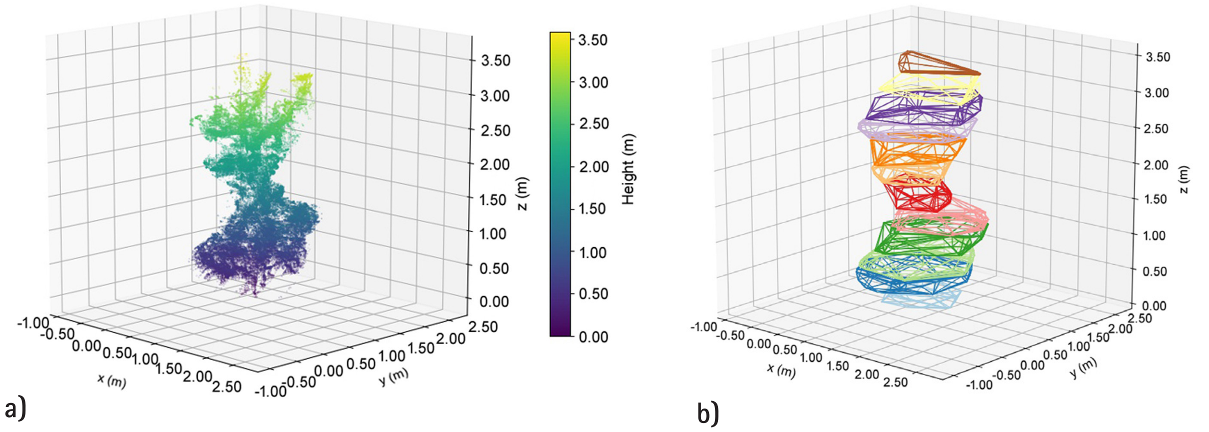

Figure 3: (a) Reconstructed 3D point cloud of an apple tree, (b) Visualization of segmented convex hull approach applied on tree point cloud (segment height 0.30 m)

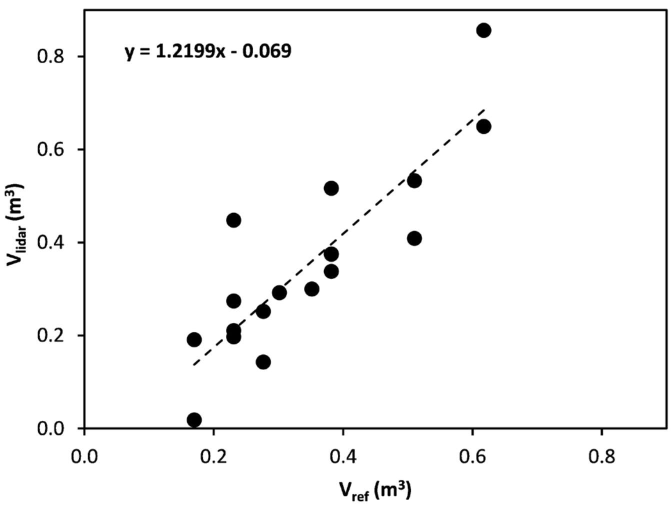

Figure 4: Linear correlation between LiDAR volume estimated by segmented convex hull approach and manually measured reference volume of corresponding tree segments

Conclusions

Although 2D mobile LiDAR systems are widely used in forestry and frequently in precision agriculture, its feasibility in horticulture is still underestimated. The analysis of a standard box coated with $BaSO_4$ assisted to determine the uncertainty in length, width, and volume estimation with Sick LMS511 pro LiDAR laser scanner. Highest RMSE were found for height and width estimation with 2.80 % and 0.91 %, respectively. Utilizing a segmented volume convex hull approach in a box and tree analysis pointed out the applicability of the method.

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