65. Performance assessment of low-cost LiDAR-based sensors and RGB-D cameras in fruit orchards

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Abstract

Knowing the geometric and structural characteristics of fruit orchards is essential for properly managing agricultural operations. Light detection and ranging (LiDAR) sensors allow for accurate 3D orchard reconstructions, although their high cost limits their adoption by farmers. In this work, the performance of several RGB-D cameras and emerging low-cost solid-state LiDAR sensors has been evaluated under real orchard conditions. Accuracies of 10–12 mm for the LiDAR sensors and 7 mm for the time-of-flight RGB-D camera have been achieved. These results open new opportunities for the development of low-cost orchard monitoring systems.

Keywords: 3D sensors, depth cameras, fruit tree, point cloud, solid-state LiDAR

Introduction

Monitoring the geometric and structural characteristics of fruit orchards is necessary for the deployment of precision fructiculture strategies. Several non-destructive technologies, such as photogrammetry and light detection and ranging (LiDAR), have become popular for the automatic characterization of tree crops (Gregorio and Llorens, 2021). Among photogrammetric techniques, structure-from-motion (SfM) stands out for its ability to generate accurate 3D reconstructions by moving an RGB camera to different positions and taking photos with significant overlap. SfM technique has been applied for plant phenotyping in outdoor conditions (Jay *et al*., 2015; Martínez-Guanter *et al*., 2019) and for in-field fruit detection (Gené-Mola *et al*., 2021; Herrero-Huerta *et al*., 2015;). However, the application of these photogrammetric techniques for orchard monitoring is limited by their high computational cost and reliance on lighting conditions. LiDAR is a robust, high-performance technology well-suited for outdoor use, relying on the emission of laser light and the detection of the backscattered signal. LiDAR sensors have been extensively applied to characterize tree crops such as pears, apples, vineyards, and olives (Escolà *et al*., 2017; Gené-Mola *et al*., 2020a; Sanz *et al*., 2018). Despite their advantages, conventional LiDAR sensors, equipped with moving mechanical components such as mirrors to direct the laser beam, are typically expensive. This high cost limits their adoption in the sector. Nowadays, there is a wide range of RGB-D cameras available on the market that provide colour, depth, and IR intensity data at a much lower cost than conventional LiDAR sensors. However, their application in monitoring fruit orchards has been limited to date due to their poor performance under daylight conditions (Bengochea-Guevara *et al*., 2017; Milella *et al*., 2019; Rosell-Polo *et al*., 2015, 2017). Additionally, the recent advent of affordable LiDAR-based sensors, typically based on a solid-state architecture with no moving parts, opens up new opportunities. The present work assesses the performance of various RGB-D cameras and emerging low-cost LiDAR sensors in producing accurate three-dimensional reconstructions

of fruit trees across varying lighting conditions. This evaluation serves as an initial step toward the development of an affordable orchard monitoring system.

Materials and methods

Field tests were performed at an experimental pear orchard located in the School of Agrifood and Forestry Engineering and Veterinary Medicine at the Universitat de Lleida (Catalonia, Spain). The canopy was trained as a fruiting wall, with a spacing of 4.5 m×1.5 m, with the rows oriented in an approximately north-south direction. The study was focused on measuring a tree located in the middle of the row, 2.9 m high and 1.3 m wide.

Three RGB-D camera types were used in this experiment: time-of-flight (ToF) (Azure Kinect DK, Microsoft, Redmond, WA, USA), active stereoscopy (RealSense D455f, Intel, Santa Clara, CA, USA) and passive stereoscopy (ZED X Mini, Stereolabs, San Francisco, CA, USA). The two evaluated LiDAR sensors (Mid-360 and Mid-70) were manufactured by Livox Technology (Shenzhen, Guangdong, P.R. China) and are characterized by emitting a non-repetitive scanning pattern. The Mid-360 is based on a mirror hybrid-solid technology and features a field of view (FoV) of 360°×59°, while the Mid-70 uses rotation-free photoelectronic components and has a circular FoV of 70.4°. Table 1 shows the specifications of the RGB-D cameras and LiDAR sensors under the configuration options used in the experiment.

As shown in Figure 1, sensor acquisition and data storage were managed by a Jetson AGX Orin embedded module (NVIDIA, Santa Clara, CA, USA). The acquisition system was powered by a high energy density 12 V lithium battery with a built-in battery management system (BMS). The sensors were located at a distance of 3.8 m from the axis of the tree row and remained static (eastwards-oriented) throughout the experiment. RGB-D and LiDAR acquisitions were made every 15 minutes between 11:00 h and 19:00 h (11 April 2024, UTC+2) and every 5 minutes between 19:00 h and 21:00 h (rapid ambient light decrease during dusk). Three different integration times (IT) of 1 s, 5 s and 10 s were used for the LiDAR acquisitions. The ambient illuminance was measured during the entire experiment by means of an automatic lux meter (PCE-LMD 10, PCE Instruments, Meschede-Freienohl, Germany) at a sampling rate of 1 Hz. In addition, 1853 photographs of the tree were taken with a handheld EOS 60D DSLR camera (Canon, Tokyo, Japan) equipped with a 5184×3456 pixel CMOS APS-C sensor. Regarding the camera lens, a Canon EF 50 mm f/1.4 USM was used. These images were used to create an accurate photogrammetric 3D reconstruction by applying SfM and multi-view stereo.

Table 1. Specifications of the evaluated sensors.

	Azure Kinect DK	RealSense D455f	ZED X Mini	Mid-360	Mid-70
Principle	ToF camera	Active IR stereo vision	Passive IR stereo vision	LiDAR	LiDAR
Range	0.5–3.86 m	0.6–6 m	0.1–8 m	0.1–70 m	0.1–260 m
RGB resolution	1280×720 px	640×480 px	1920 × 1080 px	–	–
Depth resolution	640×576 px (NFOV mode)	640×480 px	(Neural mode)		
Frame or point rate	30 fps	15 fps	30 fps	200 000 points/s	
Integration time	-	-	-	1 s, 5 s, 10 s	
Field of view	90°×59°	87°×62°	110° × 80°	360°×59°	70.4° (circular)
RGB and depth	75°×65°	87°×58°			

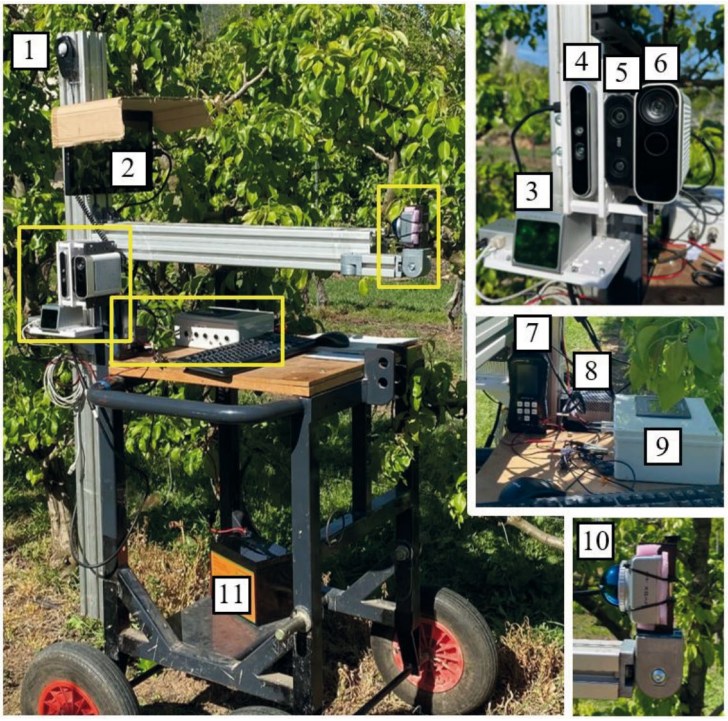

Figure 1. Set-up of the acquisition system. (1) Light sensor; (2) touchscreen; (3) Livox Mid-70; (4) Intel RealSense 455f; (5) Stereolabs ZED X Mini; (6) Microsoft Azure Kinect DK; (7) PCE-LMD 10 Lux meter; (8) Jetson AGX Orin; (9) connection box and battery monitor; (10) Livox Mid-360; (11) lithium battery.

The photogrammetric reconstruction was used as reference to register (using rigid transformations) and segment the 3D point clouds captured by the different sensors. Once registered, a region of interest (ROI) was defined for all the point clouds. The RGB-D cameras and low-cost LiDAR sensors were evaluated in terms of resolution, precision, and accuracy following the methodology proposed by Gené-Mola *et al.* (2020b). Regarding resolution, the number of points and the average point cloud density were computed for each acquisition. Accuracy was assessed by calculating the average Euclidean distance between each point in the evaluated cloud and its nearest point in the reference cloud (photogrammetric reconstruction). To measure this distance, the software CloudCompare v2.13.2 (EDF R&D, Paris, France) was used. The precision or repeatability was evaluated by computing the distances between point clouds corresponding to different replicates of the same acquisition.

Results and discussion

A qualitative analysis revealed that the most faithful 3D point clouds were provided by the Azure Kinect camera and by the LiDAR sensors. Therefore, only the Azure Kinect and the LiDAR sensors were analysed in the subsequent evaluations. Even so, it is noteworthy that the stereovision RGB-D cameras demonstrated robust performance under different lighting conditions, and their low power requirements make them ideal for numerous agricultural robotics applications.
Figure 2 presents several point clouds acquired by the Azure Kinect camera and by the Mid-360 and Mid-70 LiDAR sensors. It is observed that the Azure Kinect was strongly affected by daylight.

Hence, only Azure Kinect acquisitions between 19:00 h and 21:00 h (illuminance ranging from 4350 lux to 0 lux) were considered. Regarding the LiDAR sensors, it can be seen how the density of the point clouds increased with integration time.

As can be seen in Figure 3, the number of points of the LiDAR acquisitions increased with the integration time, but it did not depend on the lighting level. Although a similar behaviour was observed for both LiDAR sensors, the Mid-70 provided clouds with a number of points one order of magnitude higher. This difference is attributed to the fact that although both sensors have the same point rate, in the Mid-70 these points are concentrated in a smaller FoV. By contrast, the Azure Kinect showed a strong direct correlation (r=0.98) between point number and illuminance. For low lighting conditions (<1000 lux), the Azure Kinect provided a number of points similar to that of the Mid-360 with an IT of 5 s.

Figure 4 shows accuracies ranging from 10 mm to 12 mm for both LiDAR sensors, with no observed dependence on illuminance or integration time. To avoid redundancy, only the accuracies for an integration time of 5 s are presented, as they are similar to those obtained for 1 s and 10 s. Therefore, the accuracy does not seem to be improved on the Mid-70 compared to the Mid-360, despite a higher number of points. Conversely, the accuracies for the Azure Kinect were progressively improved as the ambient light decreased, achieving 7 mm for less than 1500 lux.

Figure 5 demonstrates that the precision or repeatability of both LiDAR sensors was not affected by illuminance and improved with longer integration times. Precision values of 8.5 mm and 4 mm (10 s of integration) were achieved by the Mid-360 and the Mid-70, respectively. Like the other metrics, the precision of the Azure Kinect exhibited a strong dependence on the illuminance, ranging from 34 mm at 4350 lux to less than 6 mm in the absence of ambient light.

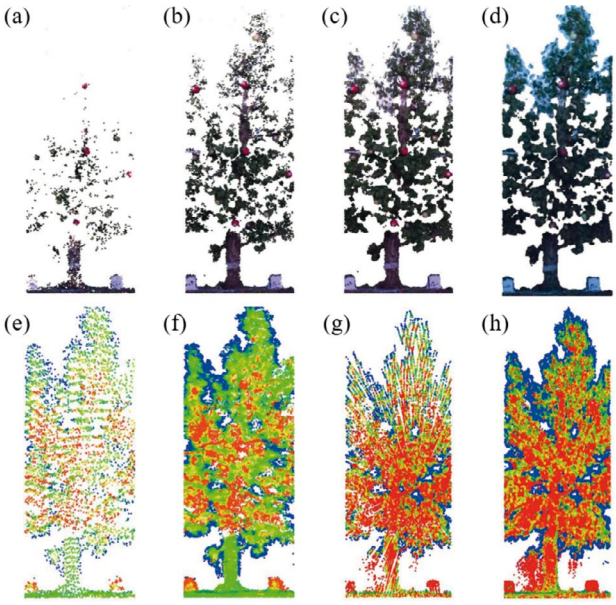

Figure 2. RGB-D point clouds acquired by the Azure Kinect camera under different lighting conditions: (a) 3151 lx, (b) 1798 lx, (c) 327 lx, (d) 2.5 lx. IR clouds acquired by the LiDAR sensors using different integration times (IT): (e) Mid-360 with IT=1 s, (f) Mid-360 with IT=10 s, (g) Mid-70 with IT=1 s, (h) Mid-70 with IT=10 s.

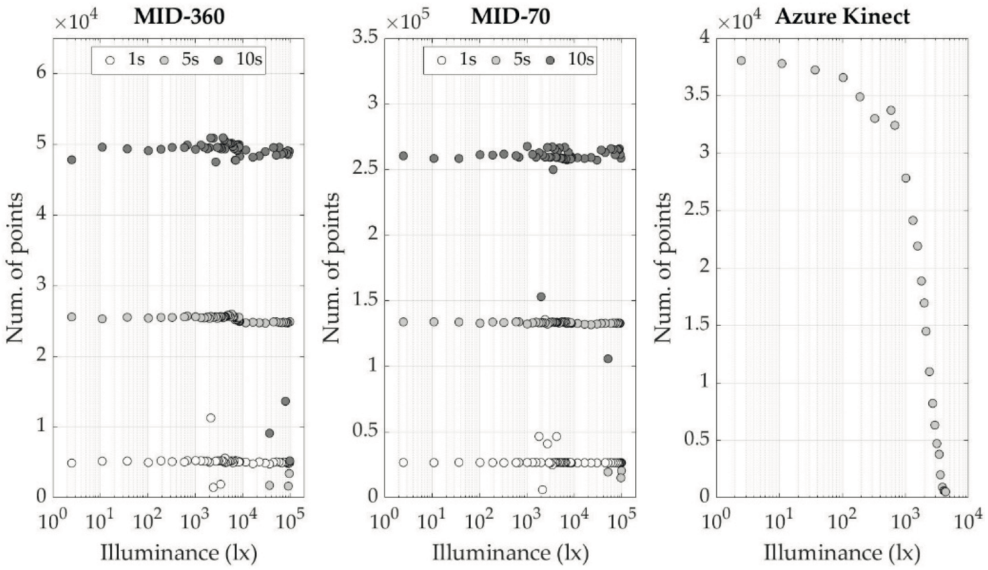

Figure 3. Evolution of the number of points acquired by the evaluated sensors as a function of illuminance. Measurements considered were from 11:00 h to 21:00 h for the LiDAR sensors, and from 19:00 h to 21:00 h for the Azure Kinect.

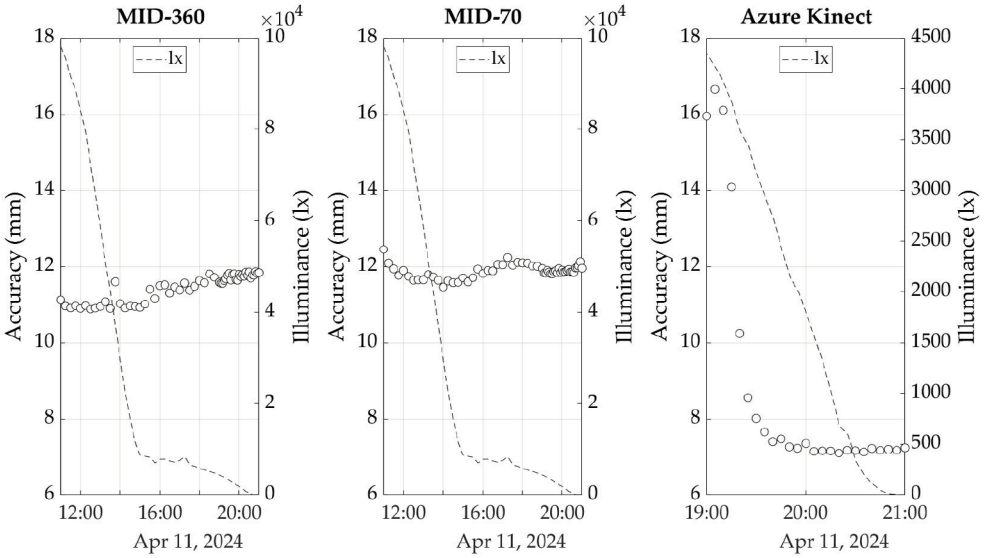

Figure 4. Evolution of the point cloud accuracy for the evaluated sensors throughout the experiment.

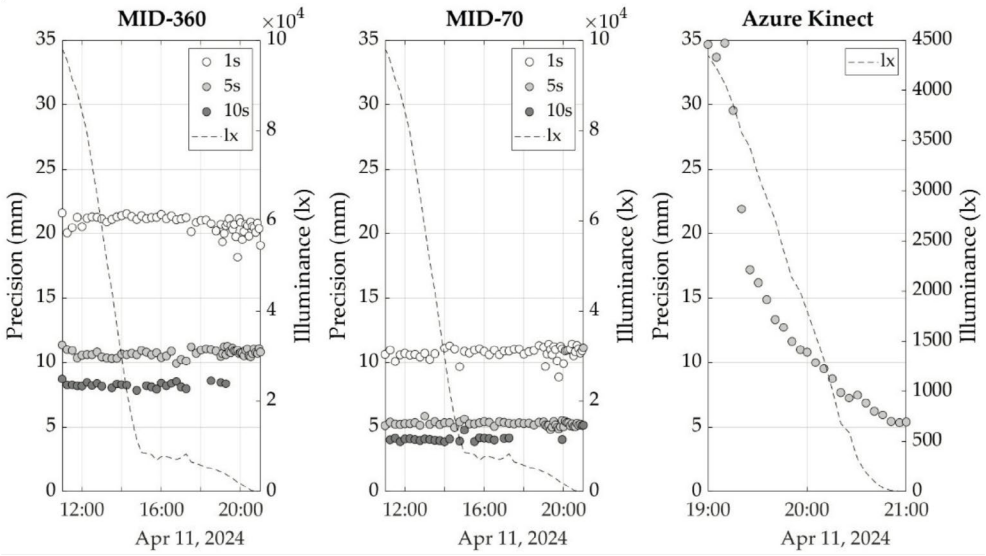

Figure 5. Evolution of the point cloud precision for the evaluated sensors throughout the experiment.

The evaluation of the LiDAR sensors demonstrated that both the Mid-360 and the Mid-70 can generate 3D reconstructions of fruit trees with a high level of accuracy, which remained unaffected by either the integration time or the illuminance. The selection of a specific LiDAR sensor will depend on the intended application. With the sensor operating as a static terrestrial laser scanner (STLS), the Mid-70 offers advantages in terms of higher point cloud density and greater precision. On the other hand, the Mid-360 is advantageous when the objective is to scan a larger area due to its wider field of view. In addition, according to the manufacturer, the non-repetitive scanning technology used by both LiDAR sensors allows for a longer integration time to increase the FoV coverage (the total area illuminated by laser beams divided by the total area in FoV) (Livox, 2024). Regarding RGB-D cameras, the one based on the ToF principle (Azure Kinect) produced reliable reconstructions of the tree. However, this camera is affected by sunlight and can only achieve accuracy, precision and point cloud density similar to that of LiDAR sensors when operating under reduced lighting conditions (<1000 lux). Although sunlight is a major limitation for field phenotyping applications, it is important to note that in this experiment the Azure Kinect camera was positioned at a distance from the tree near to its maximum range. The authors have observed that its performance under sunlight improves significantly when the distance is reduced. However, shorter distances may result in the sensor not capturing the entire tree, depending on its height. The Azure Kinect provides both colour and depth data, which can be advantageous in applications where, in addition to the geometric and structural characterization of trees, segmentation and/or detection of vegetative organs (fruits, branches, etc.) is required.

Conclusions

The tested low-cost LiDAR sensors presented accuracy and precision values that makes them suitable for tree crops characterization. Most importantly, its behaviour is robust to changes in lighting conditions. For its part, the Azure Kinect (ToF RGB-D camera) is an alternative that provides additional colour data with similar point cloud densities, accuracy, and precision. However, its performance was significantly affected by sunlight. As future work, these low-cost sensors will be

mounted on a mobile terrestrial platform to complete 3D reconstructions of fruit orchards. The availability of cost-effective systems for monitoring fruit orchards could accelerate the adoption of these technologies by the sector, while also contributing to the reduction of fertilizer, pesticide, and water usage through a deeper understanding of the plantations and their variability.

Acknowledgements

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