Preliminary Results of a Low-Cost Portable Terrestrial LiDAR Based on ICP-SLAM Algorithms. Application to Automatic Forest Digital Inventory

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Abstract. Traditional terrestrial forest inventory methods are being replaced by forest monitoring strategies closely associated with the rise of remote sensors such as Portable Terrestrial LiDAR (PTL). Off-the-shelf PTL devices produce high-quality point clouds by applying SLAM (simultaneous location and mapping) algorithms supported by both global navigation satellite system (GNSS) and inertial navigation system (INS) data. However, they are still excessively expensive to allow widespread use by many users. This work aims to develop and validate a low-cost backpack PTL system based on an Ouster OS0-32™ LiDAR. A new algorithm based on the iterative closest point (ICP) method was applied to obtain the final point cloud. Neither GNSS data nor INS data were used to generate the reconstructed point cloud. The suitability of the point cloud produced to extract significant dendrometric attributes from the forest inventory was evaluated in five square plots 25 m side of reforested Aleppo pine located in "Sierra de María-Los Vélez" (Almería, Spain). These plots were previously scanned with a Faro Focus3D X-330™ static terrestrial laser scanner (TLS). The software UALtree was used to automatically extract tree location, tree height and normal diameter from the PTL-derived point cloud, yielding, as expected, less accurate results than those provided by TLS, mainly due to the high presence of remaining noise in the PTL point cloud. These results are promising enough to continue with this line of research towards obtaining a low-cost LiDAR mobile forest mapping system based exclusively on ICP-SLAM approaches.

Keywords: Forest Inventory, Portable Terrestrial LiDAR, SLAM, ICP, Individual Tree Detection, Dendrometric Features.

1 Introduction

The continuous development of ground-based LiDAR systems has managed to digitize forests at the centimeter level, also significantly increasing the precision, efficiency, and quantity of products potentially achievable compared to traditional forest inventories based on "manual" sampling procedures [1]. These ground-based systems are classified into two categories: terrestrial laser scanners (TLS) and the more-recently-developed portable terrestrial LiDAR (PTL).

TLS are stationary systems fixed on a tripod that present an invariant global coordinate system that allows averaging the laser range of different pulses at the same target point. This technique produces very accurate and well-reconstructed point clouds (PCs) from which dendrometric features can be conveniently extracted in the context of a tree-centric approach [2]. However, the occlusion effect due to trees/shrubs continues to limit the extraction of forest attributes at the plot level, forcing a less efficient multi-scan approach subject to registration errors [3].

PTL devices operate mounted on mobile platforms that move through the forest, which helps reduce the occlusion problems presented by single scan TLS systems [4]. They use some form of a Simultaneous Localization and Mapping (SLAM) algorithm to reference laser distance measurements in 3D space while the device is moving and without the need for a global navigation satellite system (GNSS). By integrating SLAM algorithms into PTL systems, usually supported by GNSS and inertial navigation systems (INS) data to increase their accuracy and robustness, foresters can obtain PCs as they walk, enabling real-time mapping in complex and changing forest landscapes. Off-the-shelf PTL devices produce high-quality point clouds, although they are still excessively expensive to allow widespread use by many users. Note that SLAM algorithms perform better when applied indoors, working poorly when applied outdoors and not counting on GNSS/INS data due to the complex and irregular features detected by the laser scanner [5].

This work aims to test a new low-cost backpack PTL system based on an Ouster OS0-32™ LiDAR to segment trees and extract some of their key dendrometric features. The final PC was reconstructed using an innovative SLAM algorithm based on the iterative closest point (ICP) method without the support of GNSS/INS data.

2 Materials and Methods

2.1 Study site and field data collection

The test was carried out in five forest plots located in the “Sierra de María-Los Vélez” Natural Park, north of the province of Almería (Spain). The plots had a square shape of 25 m side and contained reforested stands of Aleppo pine (*Pinus halepensis* Mill.) with variable density, tree height and presence of shrubs and low vegetation (Table 1). This forest typology is very representative of Mediterranean forests.

Table 1. Dasometric characteristics of the five reference plots. Number of trees (N), tree density (D), vegetation cover (VC), plot-level uniformity index ($PH^3 50$) (from 0.37 to 0.50 for homogeneous plots), basal area (G), Lorey´s height (L_h), and mean slope (M_{slope}). (*) Homogeneous plot.

Reference plot	N	D (trees/ha)	VC (%)	$PH^3 50$	G (m^2/ha)	L_h (m)	M_{slope} (°)
18A1P	34	544	55.17	0.30	26.31	7.45	12.77
16A2P	28	448	45.4	0.30	15.33	6.65	15.92
13A3P	21	336	37.32	0.27	10.55	6.68	12.63
13A1P	23	368	40.57	0.24	8.28	5.55	16.55
10B1P	18	288	51.69	0.38 (*)	24.32	10.57	9.61

The traditional inventory fieldwork was carried out in June 2021. It consisted of locating the position and measuring the DBH (trunk diameter at 1.3 m from the ground) of each tree. A pair of Emlid Reach RS2 GNSS RTK multiband receivers allowed the precise location of each tree in the field to measure its DBH using a tape measuring Tree height was measured on a high-resolution canopy height model derived from accurate UAV image-based PCs.

The TLS fieldwork campaign using a *Faro*™ Focus3D X-330 device was conducted in July 2021, applying a workflow fully described in [6]. The TLS PCs obtained in this campaign were taken as reference to test the performance of the tested low-cost PTL.

The PTL fieldwork was accomplished on November 29, 2023. The low-cost backpack PTL system was based on an Ouster OS0-32™ LiDAR with 32 channels, ultra-wide 90º vertical FOV and range of up to 75 m at 80% Lambertian reflectivity. The backpack also consisted of a harness to secure the device to the user's back, an industrial computer with a 2 TB hard drive to store data, and a 12V/26Ah rechargeable gel battery. The system can be managed remotely using a simple Android smartphone connected to the computer's WLAN and using the free "Mobile SSH" Android app to enter command lines. The PTL trajectories followed a single parallel-line pattern, also trying to produce a closed loop to reduce SLAM drift. The time taken to complete each plot ranged from four to eight minutes. Five white target spheres (15cm diameter) located on 1m long metal rods were distributed in each plot and used to georeferencing the final PC in the Spanish geodetic datum.

The PTL PC reconstruction from raw data was faced by using the MOdular Localization and mApping (MOLA) framework, initially presented in [7] and recently updated with the novel ICP-SLAM module whose structure is briefly described next.

Range data from the LiDAR is processed by the vendor’s ROS driver, which takes individual points and packs them into “scans” covering a complete 360 degrees horizontal field of view. Scans are then processed one by one, applying to them a configurable pipeline defined with the open-source MP2P-ICP library. The main steps of this pipeline include: (1) undistort the incoming scan by using the per-point timestamps to extrapolate the latest estimated sensor pose and velocity (both linear and angular); (2) selectively remove points that are too close or too far in order to avoid ICP artifacts trying to match moving objects as the person who is carrying the sensor; (3) downsample the point cloud (one point per 1x1x1m voxel) to alleviate the strongly uneven sampling of the scene by rotatory LiDARs; (4) optimization of the current sensor pose via a custom ICP point-to-point algorithm implementation using robust loss functions against a local point cloud map; (5) update of the local PC with a different (less decimated) version of the incoming scan.

We save the estimated SE(3) trajectory of the carried sensor along with a selected subset of all original LiDAR scans (before entering the pipeline), which we call keyframes. After the mapping session ends, those keyframes can be used to reconstruct a denser PC (decimation with 10x10x10cm voxels) with a different MP2P-ICP pipeline, leading to the results shown in the next sections.

2.2 Point cloud processing and dendrometric features extraction

The following workflow was applied to the TLS and PTL PCs:

1) The TLS and low-cost PTL PCs were georeferenced using the ETRS89 coordinates of the target spheres measured by GPS-RTK during fieldwork.

2) PC was subsampled using the “Spatial” method implemented in CloudCompare v2.12.0 (minimum space between points of 2 cm). Next, each PC was automatically classified into ground and non-ground points applying the algorithm TIN iterative approach implemented into Agisoft Metashape using the following setting parameters: cell size = 10 m, distance = 0.3 m, and angle = 30°.

3) UALtree, a Matlab® software developed by our research group, was used to automatically obtain a prior tree segmentation from which to extract tree location, tree height and DBH. A full description of this software can be found in [6].

4) Tree detection accuracy was addressed by matching the trees recorded in the field to the trees extracted from each plot. The closest field tree within a 3 m search radius was matched to each UALtree detected tree. Based on the matching results, recall (*r*), precision (*p*), and F1-score (*F1 = (2*r*p)/(r+p)*) were computed. Tree height and DBH estimates accuracy were evaluated by applying some error statistics (Tables 3 and 4) to each pair of observed values (field data) and estimates (automatically extracted by UALtree) for each matched tree. Residuals were obtained by subtracting the observed H or DBH from the estimated H or DBH.

3 Results

Table 2. Tree detection assessment for Faro Focus3D X-330™ and low-cost PTL PCs.

	Faro Focus3D			Low-cost PTL		
Reference plot	Precision	Recall	F1-score	Precision	Recall	F1-score
18A1P	100%	100%	100%	96.55%	82.35%	88.89%
16A2P	92.31%	85.71%	88.89%	96.15%	89.28%	92.59%
13A3P	90%	85.71%	87.80%	100%	85.71%	92.31%
13A1P	90%	78.26%	83.72%	85%	73.91%	79.07%
10B1P	90%	100%	94.74%	80%	88.89%	84.21%
Average	93.59%	94.41%	93.78%	91.54%	84.03%	87.41%

Table 3. Accuracy of the estimate of tree height (H) according to Mean error, Median error, RMSE, relative RMSE (RMSE/mean observed H), and Pearson correlation coefficient (r).

	Faro Focus3D					Low-cost PTL				
Reference plot	Mean (m)	Median (m)	RMSE (m)	Relative RMSE	r	Mean (m)	Median (m)	RMSE (m)	Relative RMSE	r
18A1P	0.10	0.22	0.57	8.26%	0.8817	-0.12	0.10	0.84	11.97%	0.6153
16A2P	0.37	0.37	0.49	7.69%	0.9532	0.44	0.52	0.67	10.29%	0.8853
13A3P	0.32	0.39	0.43	6.89%	0.9750	0.25	0.46	0.79	13.04%	0.7655
13A1P	0.38	0.30	0.47	9.05%	0.9701	0.56	0.43	0.65	12.24%	0.9592
10B1P	0.21	0.27	0.55	5.25%	0.8731	-1.76	-1.84	2.12	20.31%	-0.0557

Table 4. Accuracy of the estimate of DBH (cm) according to Mean error, Median error, RMSE, relative RMSE (RMSE/mean observed DBH), and Pearson correlation coefficient (r).

	Faro Focus3D					Low-cost PTL				
Reference plot	Mean (cm)	Median (cm)	RMSE (cm)	Relative RMSE	r	Mean (cm)	Median (cm)	RMSE (cm)	Relative RMSE	r
18A1P	-0.05	-0.41	2.03	10.44%	0.9030	-2.80	-3.26	4.29	21.85%	0.6409
16A2P	0.23	0.02	2.37	14.09%	0.7562	0.86	0.04	2.76	16.44%	0.5161
13A3P	0.84	1.00	2.51	14.34%	0.8975	2.97	3.06	4.46	26.02%	0.8137
13A1P	1.71	0.75	5.81	39.36%	0.5871	4.16	3.82	6.52	41.70%	0.4703
10B1P	-0.14	-0.24	1.55	5.40%	0.9692	-0.54	0.62	4.10	14.12%	0.6714

4 Discussion

As can be seen in Table 2, PTL PCs provided better precision than recall, i.e. 91.54% and 84.03% on average, respectively, pointing to a scenario of low over-segmentation (commission error) and slightly high under-segmentation (omission error). In any case, the results obtained with the PTL PCs were quite good compared to those provided by TLS, although the less noisy TLS PCs allowed the omission error to be significantly reduced to average values below 6%. In addition, the F1-score average results for the two types of PCs were only about six percentage points apart, while the plot 13A1P, which presented the greatest slope and was most heterogeneous (Table 1), showed the lowest recall ratio for both kind of PCs.

Table 3 shows the results of tree height estimates accuracy. In this case, the results extracted from the TLS and PTL PCs were significantly different, with an average relative RMSE of 7.43% and 13.57%, respectively. Note that a significant part of the error was centered on plot 10B1P (up to 20.21% of the relative RMSE), which was a fairly homogeneous plot with trees very similar in height (Table 1). These homogeneous trees caused clear occlusion problems among themselves along the PTL trajectory, causing an average error of up to -1.76 m (the apex of the tree was not visible) and a Pearson correlation coefficient of -0.05. A solution to this problem would be to resort to a trajectory that follows a double parallel line-pattern. This would increase to approximately double the time needed to collect data from a plot, but the area of the plot would be systematically covered and all trees in the plot would be covered on all sides.

It is widely known that PTL devices, even the most sophisticated ones such as ZEB Horizon, exhibit biases in DBH extraction. Table 4 depicts that the DBH values automatically extracted from the TLS and PTL PCs presented average relative RMSE of 16.73% and 24.03%, respectively, usually overestimating the actual values. Generally, this was due to the presence of low branches and understory vegetation that was not adequately filtered out by the UALtree software. This situation was very evident in plot 13A1P. Furthermore, a significant component of the error in the case of PTL PCs could be attributed to the presence of very strong spatial noise that converted a ring of points (visible in the TLS data) into a disk of points that it did not even define a clear circle.

5 Conclusions

The results presented in this preliminary work have shown that it is feasible to use the proposed ICP-SLAM algorithm and the low-cost PTL hardware system to construct spatially coherent point clouds from which to extract relevant forest information at the tree level. The performance in tree segmentation and location can be considered quite good and almost comparable to that provided by high-cost TLS systems. However, the noisy nature of the SLAM-reconstructed PTL point cloud, due to the difficulties in generating the composite cloud of individual scans co-registered through the SLAM algorithm, made it more difficult to accurately extract dendrometric features such as tree height and DBH. While tree height estimates could be improved by simply using a denser trajectory pattern to avoid occlusions in very homogeneous forest plots (e.g., a double parallel-lines pattern), improving DBH estimates would require working in at least two directions. First, improving the extraction algorithm by trying other approaches. Second, significantly reduce the noise of the point cloud reconstructed from the ICP-SLAM algorithm by exploring other local map structures, e.g. surfels (“surface elements”), which implicitly average out the noise from LiDAR points.

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