

Article

Advancing Forest Plot Surveys: A Comparative Study of Visual vs. LiDAR SLAM Technologies

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Abstract: Forest plot surveys are vital for monitoring forest resource growth, contributing to their sustainable development. The accuracy and efficiency of these surveys are paramount, making technological advancements such as Simultaneous Localization and Mapping (SLAM) crucial. This study investigates the application of SLAM technology, utilizing LiDAR (Light Detection and Ranging) and monocular cameras, to enhance forestry plot surveys. Conducted in three 32 × 32 m plots within the Tibet Autonomous Region of China, the research compares the efficacy of LiDAR-based and visual SLAM algorithms in estimating tree parameters such as diameter at breast height (DBH), tree height, and position, alongside their adaptability to forest environments. The findings revealed that both types of algorithms achieved high precision in DBH estimation, with LiDAR SLAM presenting a root mean square error (RMSE) range of 1.4 to 1.96 cm and visual SLAM showing a slightly higher precision, with an RMSE of 0.72 to 0.85 cm. In terms of tree position accuracy, the three methods can achieve tree location measurements. LiDAR SLAM accurately represents the relative positions of trees, while the traditional and visual SLAM systems exhibit slight positional offsets for individual trees. However, discrepancies arose in tree height estimation accuracy, where visual SLAM exhibited a bias range from −0.55 to 0.19 m and an RMSE of 1.36 to 2.34 m, while LiDAR SLAM had a broader bias range and higher RMSE, especially for trees over 25 m, attributed to scanning angle limitations and branch occlusion. Moreover, the study highlights the comprehensive point cloud data generated by LiDAR SLAM, useful for calculating extensive tree parameters such as volume and carbon storage and Tree Information Modeling (TIM) through digital twin technology. In contrast, the sparser data from visual SLAM limits its use to basic parameter estimation. These insights underscore the effectiveness and precision of SLAM-based approaches in forestry plot surveys while also indicating distinct advantages and suitability of each method to different forest environments. The findings advocate for tailored survey strategies, aligning with specific forest conditions and requirements, enhancing the application of SLAM technology in forestry management and conservation efforts.

Keywords: forest plot survey; SLAM; LiDAR; accuracy verification



Citation: Guan, T.; Shen, Y.; Wang, Y.; Zhang, P.; Wang, R.; Yan, F.

Advancing Forest Plot Surveys: A Comparative Study of Visual vs. LiDAR SLAM Technologies. *Forests* **2024**, *15*, 2083. <https://doi.org/10.3390/f15122083>

Academic Editor: Nikolay S. Strigul

Received: 12 October 2024

Revised: 15 November 2024

Accepted: 23 November 2024

Published: 26 November 2024



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1. Introduction

Promoting the development of forestry requires a transformation in the forestry development model, advancing the integration of the forestry industry, and improving the level of forestry management [1]. Forestry management planning necessitates accurate and up-to-date data to describe the current state of forest development [2]. Continuous forest inventory work enables the efficient and precise acquisition of forest information, which is crucial for understanding the current status and trends in forest resources [3,4]. Ideally, a forest inventory involves a complete survey of every tree in the forest area. However, this is challenging due to the large-scale nature of forestry operations. Sampling is a method based

on probability theory [5]. Forest plot surveys employ a sampling approach, selecting suitable plots within the survey area and measuring the trees within these plots to extrapolate overall forest data, serving as a significant means of continuous forest inventory [6].

Traditional survey techniques often involve manual measurements using tools such as DBH calipers and clinometers. With technological advancements, survey methods have become increasingly intelligent and digitized, incorporating sensors such as LiDAR, cameras, drones, and other devices, thereby mainstreaming survey solutions and algorithms [7,8]. SLAM technology, in particular, allows for real-time mapping and pose estimation in unknown environments, enabling sensors to intelligently perceive the forest environment during plot surveys and create detailed point cloud maps for extracting and measuring individual tree factors [9,10].

LiDAR is an active remote sensing method that measures distances accurately by emitting laser pulses and analyzing the returned energy. This technology penetrates the forest canopy, providing information about the vertical and horizontal structure of the forest, making it an efficient method for forest plot surveys. Depending on its platform, LiDAR can be categorized as spaceborne, airborne, or ground-based, each catering to different survey needs. Ground-based LiDAR, or Terrestrial Laser Scanning (TLS), has been extensively researched and is commonly used in plot surveys [11–13].

More recently, mobile laser scanning (MLS) devices have been introduced in forestry, offering greater convenience by overcoming challenges such as size constraints and limited scanning angles [14,15]. These mobile systems typically integrate LiDAR scanners with an Inertial Measurement Unit (IMU) and a Global Navigation Satellite System (GNSS) [16–18]. However, forest environments often present challenges such as poor GNSS signal reception, leading to significant positioning errors. Handheld mobile laser scanning (HMLS) has been employed to address these challenges, with SLAM technology enabling environment perception and map construction without GNSS signals [19]. With the continuous advancement of smart mobile devices, especially the application of LiDAR sensors in new devices such as the iPhone and iPad, forestry survey methods are undergoing significant changes. In contrast, the use of LiDAR sensors combined with the mobile cameras of iPhones and iPads provides new technological support for forestry surveys, making forest environment perception and mapping more efficient and accurate [20].

Survey methods based on vision sensors primarily utilize close-range photogrammetry and visual SLAM technology. Close-range photogrammetry involves capturing images or videos for photogrammetric calculations to obtain the size and shape of target objects [21]. Visual SLAM technology, combined with compact mobile devices, has also been used for forest inventory work, offering an innovative approach to measure DBH, stem density, and volume [22–24]. This study aims to utilize both LiDAR SLAM and visual SLAM-based survey approaches to collect data and conduct experimental tests in forest plots. The objective is to investigate the differences in accuracy, efficiency, and suitability for forest surveys between these different survey approaches.

2. Study Area

This study is conducted in Linzhi City, located in the Tibet Autonomous Region, China. The research area, situated on the Qinghai-Tibet Plateau, boasts an average altitude of approximately 3000 m. It experiences an average temperature of around 9 °C and receives an average annual rainfall of 692.5 mm. The vegetation within this area is notably diverse, spanning tropical and subtropical to temperate and even alpine types. For this research, three artificial forest plots were selected, each measuring 32 × 32 m. The distribution and overview of these plots are illustrated in Figure 1. The plots demonstrate variability in tree quantity, density, average DBH, and diameter class distribution. Plot 1 is a monoculture of *Populus × beijingensis* W. Y. Hsu with an average DBH of 32 cm, featuring a tree density of 664 trees per hectare (N/ha). Plot 2, a mixed forest, is primarily composed of *Acer buergerianum* Miq. with an average DBH of 19.4 cm, mainly ranging within the 5–20 cm diameter class. Plot 3, another monoculture of *Populus × beijingensis* W. Y. Hsu, shows

a lower tree density of 313 N/ha. Detailed characteristics of each plot are presented in Table 1.

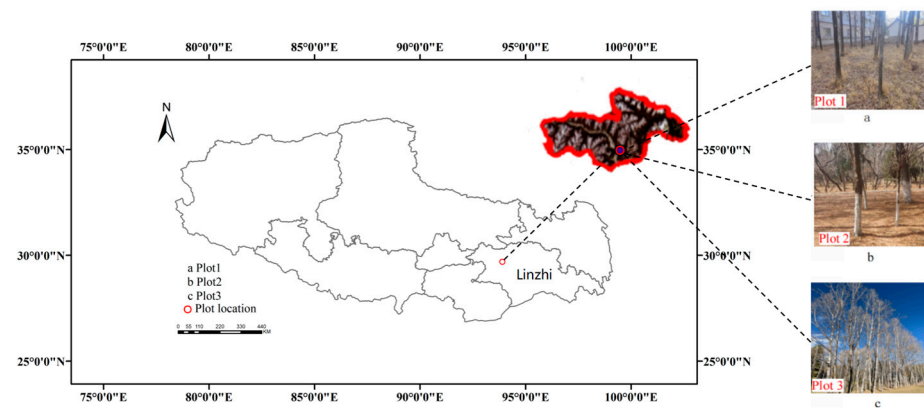


Figure 1. Study area.

Table 1. The condition of the plot.

	DBH Range (cm)	Avg. DBH (cm)	Trees [5,10)	Trees [10,20)	Trees [20,30)	Trees [30,40)	Trees [40,80)	Total	Tree Density (N/ha)	Number of Tree Species	Dominant Tree Species
Plot 1	8.3–63.3	32	1	8	22	21	16	68	664	1	<i>Populus × beijingensis</i> W. Y. Hsu
Plot 2	5.5–42.7	19.4	6	26	6	7	2	47	459	4	<i>Acer buergerianum</i> Miq.
Plot 3	15–74.2	31.7	0	3	16	4	9	32	313	1	<i>Populus × beijingensis</i> W. Y. Hsu

Avg. DBH represents the average diameter at breast height (DBH) value for the plot; “Trees [5,10)” indicates the number of trees with a diameter at breast height (DBH) in the range of 5 cm (inclusive) to 10 cm (exclusive).

3. Methods

3.1. LiDAR SLAM

The framework of the SLAM system can be broadly categorized into five components: sensor data acquisition and processing, front-end odometry, back-end optimization, loop closure detection, and map construction. Initially, sensor data is collected and processed. This data is then analyzed by front-end odometry to swiftly estimate the pose transformation between consecutive data frames, a process that may introduce accumulated errors. The back-end optimization is tasked with global trajectory optimization, refining poses through graph optimization or filtering algorithms to create globally consistent maps. Throughout this procedure, loop closure detection is perpetually active to identify previously visited scenes, facilitating loop closure and mitigating accumulated errors.

This study utilizes a handheld laser scanner, as depicted in Figure 2, equipped with Inertial Measurement Unit (IMU) sensors for acquiring mobile laser scanning (MLS) data. The SLAM100 handheld scanner (Shenzhen Feima Robotics Company, Shenzhen, China) is chosen for this purpose, featuring a 16-line laser radar sensor, inertial sensors, and three cameras. The LiDAR and IMU sensors are employed for scanning and constructing point cloud maps, whereas the cameras are used to capture photographs of the plots during the survey, enabling the generation of panoramic views. This instrument boasts a maximum measurement range of 120 m, a laser field of view angle of $270^\circ \times 360^\circ$, and a relative accuracy of 2 cm.



Figure 2. Handheld laser scanning device.

We use a LiDAR SLAM algorithm tightly coupled with LiDAR and IMU sensors to construct point clouds of the plot [25]. The algorithm is founded on a factor graph tightly coupled framework for laser inertial odometry, optimizing sensor fusion and global optimization. It employs an efficient scan matching method based on a sliding window approach, achieving real-time performance by selectively incorporating new keyframes into a fixed-size set of previous sub-keyframes. The IMU records the sensor's acceleration and angular velocity at a high frequency to estimate the LiDAR's state. Through pre-integration, the algorithm estimates motion to correct point cloud distortion, providing an initial position and orientation for the LiDAR odometry [26].

The algorithm attains tightly-coupled laser-inertial odometry through smoothing and mapping by integrating laser and inertial measurements within a factor graph framework. It constructs a factor graph that amalgamates multiple sources of input, thus optimizing overall mapping performance by continuously incorporating laser and inertial information as factors. Initially, the algorithm segments and preprocesses the acquired point cloud by distinguishing between ground and non-ground points. Following segmentation, non-ground points are further classified into edge and planar points based on their curvature values [27]. Once feature points are identified, matching based on these points is performed to compute relative pose transformations. The sensor's relative pose is deduced using IMU measurements to construct a local map. Subsequent steps include registration optimization, loop detection, and graph optimization, culminating in the publication of laser odometry and the construction of a point cloud map.

The overall working principle of using a handheld LiDAR scanner based on LiDAR SLAM for forest plot surveys involves first determining the starting point and scanning route based on the plot conditions. In this study, we primarily used a central starting point with a row-by-row scanning route. After conducting LiDAR scanning within the plot, the LiDAR SLAM algorithm is utilized to create a point cloud map of the plot. Thereafter, LiDAR360 (V7.2) software is employed to calculate individual tree parameters such as DBH, position, and tree height within the plot, and Origin 2022 software is used to analyze and present results. The complete workflow is illustrated in Figure 3.

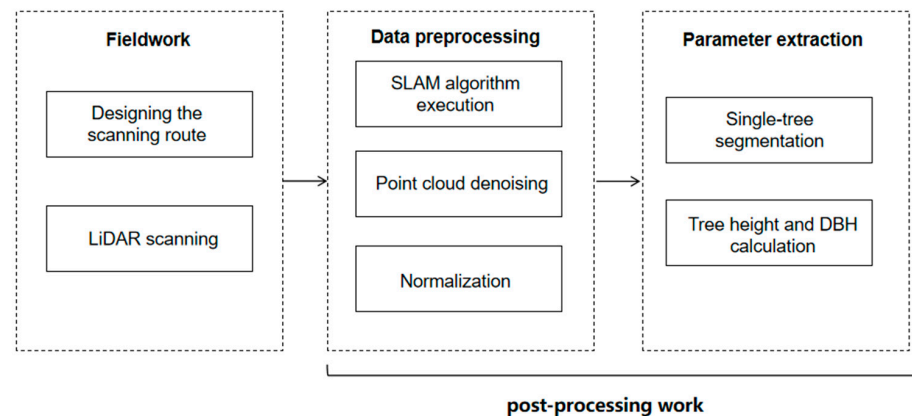


Figure 3. The measurement process of the LiDAR SLAM method.

3.2. Visual SLAM

The visual SLAM-based tree measurement system in this study uses the smartphone tree measurement system developed by Fan et al. in 2023 [28], based on monocular SLAM algorithms. The system employs a CCD array camera as the observation sensor and an IMU as the motion sensor. The advantage of the CCD array camera lies in its minimal pose estimation error over long durations and distances, making it more suitable for widespread adoption compared to other tree measurement systems based on RGB cameras or TOF cameras. The IMU excels in providing accurate pose estimation over short durations and distances. The fusion of these two sensors is one of the mainstream SLAM systems currently in use. The equipment is shown in Figure 4.

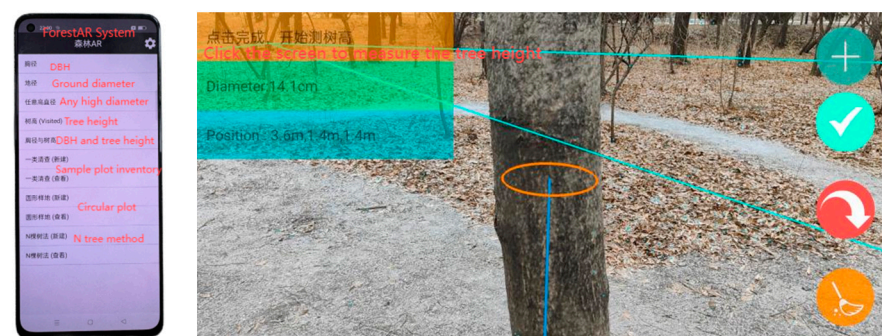


Figure 4. Visual SLAM tree measurement system.

The equipment integrates the SLAM system into a smartphone and incorporates an augmented reality module to enhance operator interaction. It is capable of constructing virtual boundaries for forest plot surveys and facilitating individual tree measurements, thereby enabling the acquisition of parameters such as diameter at breast height (DBH), tree height, and the position of individual trees within the plot. In practical operations, investigators first need to click on the screen to confirm the plot center point and the true north direction to establish the coordinate system and plot boundaries. Once this is completed, they measure each tree's diameter at breast height (DBH) and height. After the measurements are finished, the system automatically generates a plot data summary table. The overall workflow is shown in Figure 5.

The system is comprised of three modules: the monocular SLAM system, the tree measurement core system, and the user interaction system. The SLAM system is tasked with sensor pose estimation and the estimation of a dense depth map of the forest plot. The tree measurement core system, receiving user commands, employs SLAM output data to execute tasks such as measuring each tree. Lastly, the user interaction module presents an augmented reality window, allowing users to interact with the tree measurement core system.

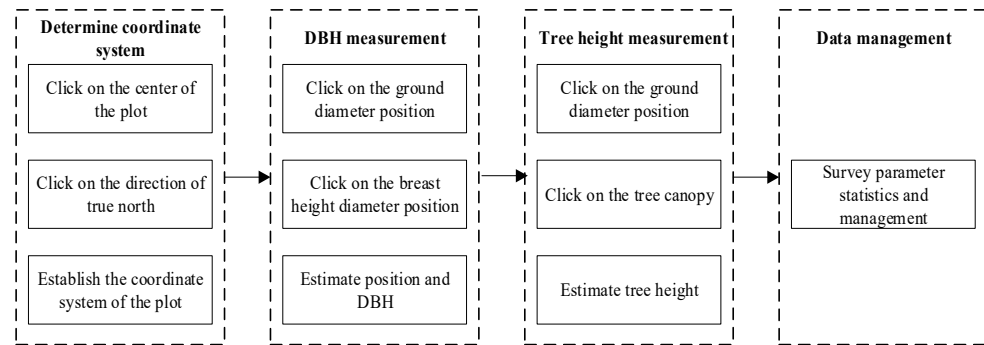


Figure 5. The measurement process of the visual SLAM tree measurement system.

3.3. Accuracy Evaluation

After completing the measurement of plot trees using handheld LiDAR and visual SLAM tree measurement equipment, we selected some traditional measurement devices to obtain reference data. These include using a diameter tape to measure the reference values for DBH (diameter at breast height) and a laser hypsometer to measure the reference values for tree height. The measurement tools are shown in Figure 6.



Figure 6. Reference measurement tools for plot data. (a) is the diameter at breast height (DBH) tape; (b) is ultrasonic tree height and range finder (Vertex III).

In this study, the accuracy of estimation was evaluated using BIAS, RMSE (Root Mean Square Error), relative BIAS (relBIAS), and relative RMSE (relRMSE) metrics, calculated with the following formulas:

$$BIAS = \frac{\sum_{i=1}^n (x_i - x_{ir})}{n}$$

$$relBIAS = \frac{\sum_{i=1}^n (x_i / x_{ir} - 1)}{n} \times 100\%$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (x_i - x_{ir})^2}{n}}$$

$$relRMSE = \sqrt{\frac{\sum_{i=1}^n (x_i / x_{ir} - 1)^2}{n}} \times 100\%$$

where x_i is an estimate; x_{ir} is the reference value corresponding to x_i ; n is the total number of trees. Both measurement methods are capable of accurately measuring breast diameters, as depicted in the scatter plots.

4. Result

4.1. DBH Accuracy

The DBH measurement accuracy for the two SLAM methods across the three plots in this study is shown in Figure 7. The x -axis represents the measured reference data, and

the y-axis represents the fitted data corresponding to each reference data point. Although there are some differences in stand density and tree diameter class distribution across the three plots, the fitted DBH values overall are distributed along the centerline of the graph, showing a high level of consistency with the reference values. The DBH measurement accuracy for the three plots in this study is shown in Table 2. For the LiDAR SLAM breast diameter measurements, the bias ranges from -0.26 to 0.7 cm, and the RMSE ranges from 1.4 to 1.96 cm. For the Visual SLAM breast diameter measurements, the bias ranges from -0.43 to -0.39 cm, and the RMSE ranges from 0.72 to 0.85 cm. The overall error for Visual SLAM is smaller than that for LiDAR SLAM, with the overall root mean square error (RMSE) being controlled within 1 cm, whereas for LiDAR SLAM, the error ranges between 1 cm and 2 cm. The DBH values measured by Visual SLAM are generally slightly smaller than the actual values, while those measured by LiDAR SLAM are relatively larger than the actual values. This discrepancy may be due to the DBH fitting method based on laser point clouds, where noise points around the tree trunk may affect the fitting process. Through the box plots in Figure 8 and the error scatter plots in Figure 9, it is observed that the overall error distribution for Visual SLAM is more evenly spread, while LiDAR SLAM exhibits relatively larger errors in estimating DBH for small-diameter trees.

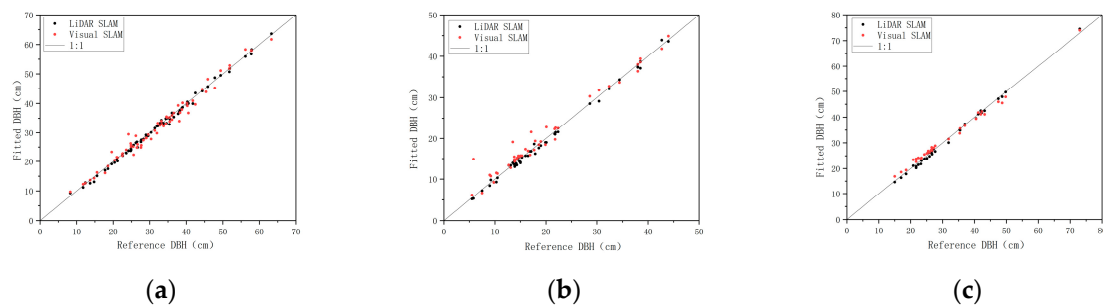


Figure 7. Estimation of DBH using the different SLAM methods. The x-axis represents the measured reference data, and the y-axis represents the fitted data corresponding to each reference data point. (a) represents the fitting results for Plot 1; (b) represents the fitting results for Plot 2; (c) represents the fitting results for Plot 3.

Table 2. Accuracies of the DBH.

	Method	BIAS/cm	relBIAS/cm	RSME/cm	relRSME/cm
Plot 1	VSLAM	-0.39	-1.40%	0.82	3.40%
	LSLAM	-0.26	-0.30%	1.64	6.01%
Plot 2	VSLAM	-0.4	-2.50%	0.72	4.45%
	LSLAM	0.77	7.40%	1.96	9.78%
Plot 3	VSLAM	-0.43	-1.70%	0.85	3.14%
	LSLAM	0.49	1.20%	1.4	5.38%

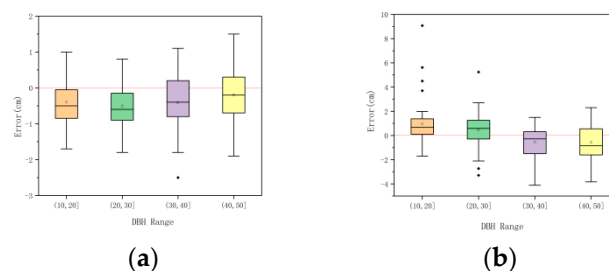


Figure 8. The errors of DBH observations for different DBH values. (a) is the error box plot for visual SLAM; (b) is the error box plot for LiDAR SLAM.

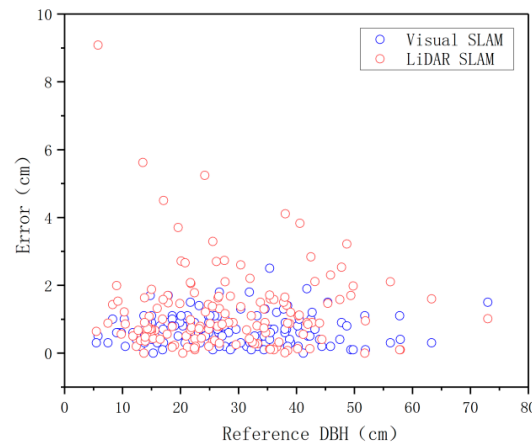


Figure 9. Scatter plot of DBH errors using the different SLAM methods.

4.2. Position Accuracy

We selected a total station as the measurement tool for tree locations in the traditional plot survey. Considering the complexity of measuring tree center positions with a total station and the potential for some error, we did not use it as the reference data for location measurements in this study. In fact, the plot environment point cloud constructed with LiDAR SLAM provides more accurate data on the relative positions of trees within the plot, better reflecting their actual locations. Therefore, our analysis of tree positions will primarily use the point cloud data generated by LiDAR as the reference. Observing the position distribution plots (Figure 10), both methods demonstrate overall positions closely aligned with the true values. Across the three plots, the various measurement methods generally perform well in expressing tree positions, accurately reflecting the actual locations of trees within each plot. The traditional total station method introduces some error in calculating tree center positions, and the visual SLAM method, due to potential cumulative system errors under certain conditions, also shows slight positional offsets for individual trees. In contrast, the LiDAR SLAM method can comprehensively capture the plot environment, providing higher accuracy in calculating the relative positions of trees.

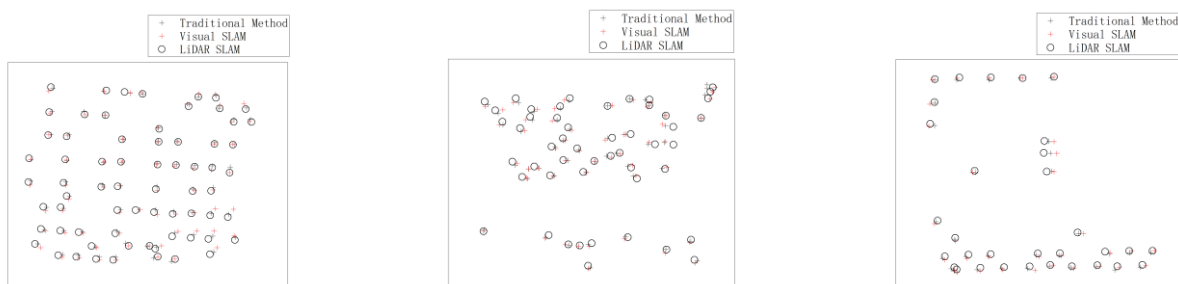


Figure 10. Scatter plot of position distribution.

4.3. Tree Height Accuracy

We used an ultrasonic tree height and range finder (Vertex III) to record the height of each tree within the plots, using these measurements as reference values to verify the accuracy of both methods. Table 3 shows the overall tree height distribution of the three plots. The fitting results for tree height measurements from both methods, as shown in Figure 11, generally align around the central line, indicating good performance. For Visual SLAM, the BIAS in tree height fitting ranges from -0.55 to 0.19 m, and the RMSE ranges from 1.36 to 2.34 m. For LiDAR SLAM, the BIAS in tree height fitting ranges from -1.27 to -0.12 m, and the RMSE ranges from 1.19 to 4.27 m (Table 4). Upon reviewing the data, it becomes apparent that in plots with lower tree density (Plots 2 and 3), the errors for both methods are similar, ranging between 1 to 2 m. However, in plots with higher tree density

(Plot 1), the errors increase significantly. This increase is primarily due to severe occlusion at the treetops in densely populated plots. The error scatter plots reveal that for Visual SLAM, errors are relatively evenly distributed across different height intervals. Conversely, for LiDAR SLAM, limited scanning angles and occlusion by branches lead to incomplete scanning of the treetops, resulting in an underestimation of tree height. Furthermore, as tree height increases, so does the error. Notably, as illustrated in Figure 12, significant deviations in error become apparent when tree height exceeds 25 m.

Table 3. Tree height distribution.

	Tree Height Range (m)				Height Range (m)	Total	Avg. Height (m)
	(0,10]	(10,20]	(20,30]	(30,40]			
Plot 1	7	11	24	26	5.2–36.5	68	25.3
Plot 2	20	26	1	0	3.7–22.2	47	11.1
Plot 3	0	6	24	2	15–30.3	32	22.3

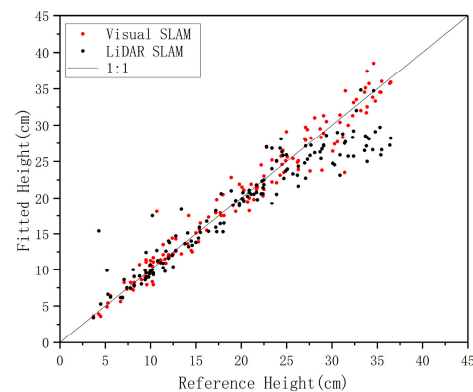


Figure 11. Tree height estimates error statistics.

Table 4. Accuracies of the tree height.

	Method	BIAS/m	relBIAS/%	RSME/m	relRSME/%
Plot 1	VSLAM	0.19	1.49%	2.34	12.60%
	LSLAM	−1.19	−0.33%	4.27	19.40%
Plot 2	VSLAM	0.3	1.43%	1.19	10.22%
	LSLAM	−0.12	3.39%	1.94	10.66%
Plot 3	VSLAM	−0.55	−2.17%	1.36	5.60%
	LSLAM	−1.27	−5.12%	1.99	7.67%

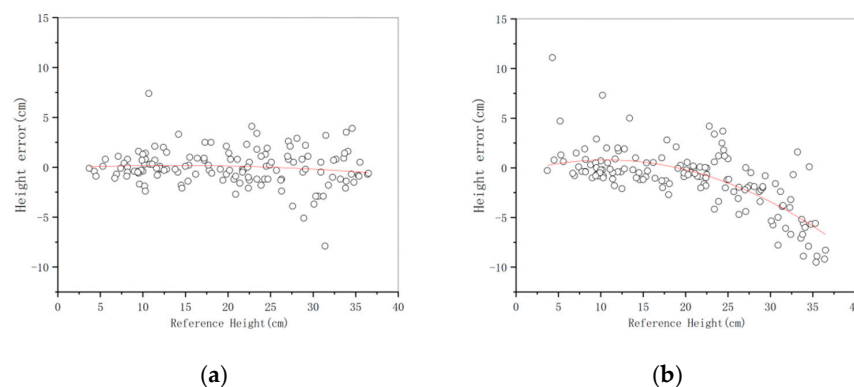


Figure 12. Scatter plot of tree height error distribution. (a) is the error distribution of tree height measurements obtained from the visual SLAM method; (b) is the error distribution of tree height measurements obtained from the LiDAR SLAM method.

4.4. Survey Efficiency

In our research, we timed each type of survey method to compare their efficiency. The overall results are shown in Table 5. The traditional survey method proved to be the least efficient, with the average time required for each plot exceeding half an hour. The time required for the survey method based on visual SLAM was half that of the traditional method, offering relatively higher efficiency. However, since the traditional and visual SLAM schemes require individual tree measurements, their measurement time and efficiency are actually influenced by the number of trees within the plot. In this study, Plot 1 has a total of 68 trees, Plot 2 has 47, and Plot 3 has 32, resulting in reduced measurement time as the number of trees decreases for these two schemes. In contrast, the LiDAR SLAM scheme maintains relatively stable overall measurement time, with the shortest time required and the highest efficiency (Figure 13). It is worth mentioning that our measurement time only accounted for the actual operation time for the two parameters, DBH and tree height, and did not include the time for instrument preparation, scheme, and route design. Additionally, due to the requirements of fieldwork, the measurement process using traditional instruments involved three surveyors working collaboratively, whereas the measurements using LiDAR SLAM and visual SLAM were completed entirely by a single person.

Table 5. Survey efficiency of each method.

	Plot 1 Duration (min)	Plot 2 Duration (min)	Plot 3 Duration (min)	Average Duration (min)	Average Efficiency (m ² /min)
Traditional methods	42	31	28	33.7	30.4
VSLAM	19	17	15	17	60.2
LSLAM	7	6	6	6.3	162.5

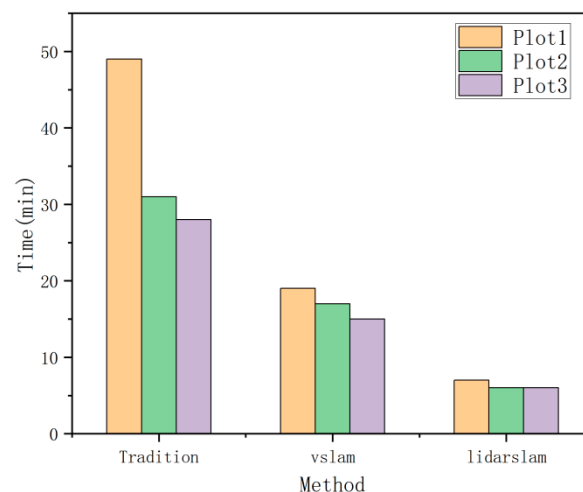


Figure 13. Survey duration of each method.

Additionally, although the LiDAR-based survey scheme has high efficiency in fieldwork, it involves a more complex post-processing phase, requiring operations such as point cloud mapping, denoising, normalization, and parameter fitting, which are time-consuming. In contrast, the visual SLAM scheme can perform parameter calculation and analysis within the system, resulting in relatively less post-processing work.

5. Discussion

5.1. The Accuracy of Plot Surveys

In this study, we conducted experimental tests on three plots using two distinct categories of SLAM algorithms for forest plot surveys. We employed a handheld LiDAR device equipped with IMU sensors to collect survey data for LiDAR SLAM and a smartphone utilizing monocular SLAM + AR technology for visual SLAM survey data. Upon analyzing the experimental data, we observed differences in accuracy between the two survey methods. The root mean square error (RMSE) for breast diameter measurements obtained from LiDAR SLAM ranged from 1 to 2 cm, while the overall accuracy of visual SLAM was notably higher, maintaining an error within 1 cm. The results of LiDAR measurement are consistent with the accuracy of DBH measured by the MLS system in previous studies. Gollob [29] achieved a root mean square error (RMSE) of 2.36 cm for DBH using the SLAM system, and Perugia obtained an RMSE of 2.45 to 2.93 cm using SLAM-based mobile laser scanning (MLS). In our study, the fitting accuracy of LiDAR corresponds to previous research, while the overall accuracy of the tree measurement device based on visual SLAM exceeds that of LiDAR equipment. In terms of tree position measurement, both survey methods showed similar accuracy, with errors ranging from 20 to 40 cm. In previous studies, it has been suggested that the accuracy of using LiDAR to measure tree height is relatively low [30]. However, in measuring tree height, both LiDAR SLAM and visual SLAM exhibited relatively larger errors, with RMSE values ranging from 1.36 to 2.34 m for visual SLAM and 1.19 to 4.27 m for LiDAR SLAM. As mentioned in the Bauwens [31] study, handheld lidar has poor scanning performance when the canopy exceeds a certain height. Our research shows that when the tree height exceeds 25 m, the height accuracy of the tree measured with LiDAR decreases. Overall, while the two survey methods demonstrated comparable accuracy in general, visual SLAM showed higher accuracy in measuring breast diameter compared to LiDAR SLAM.

5.2. Forest Environment Adaptability

The two methods of forest plot investigation differ significantly in their approach to data collection. The handheld LiDAR, utilizing LiDAR SLAM technology, merely requires a scan around the site following a pre-planned route to complete the data collection process. In contrast, the tree-measuring smartphone necessitates individual measurements for each tree within the site, demanding a more hands-on approach for each tree. Thus, in terms of fieldwork efficiency, LiDAR SLAM significantly outperforms the tree-measuring smartphone. However, the tree-measuring smartphone has the advantage of calculating data in real-time during the measurement process, which eliminates the need for post-processing. Conversely, the LiDAR SLAM algorithm requires relatively complex post-processing to extract the corresponding data for the site.

When using the tree-measuring smartphone for diameter measurements, it is essential to maintain a relatively close distance to the target tree. This requirement can present challenges, particularly if the terrain within the plot is uneven or if accessing the target tree is difficult. On the other hand, LiDAR technology can perform scans from a greater distance, making it more adaptable to complex forest environments. However, LiDAR scanning may face limitations in areas with high tree density or very tall trees. Such limitations are primarily due to the obstruction caused by tree branches and the constraints of scanning angles, which can result in incomplete scanning of treetops and affect the scanning results. Volume measurement of trees in forest plots is crucial for calculating carbon storage and biomass, and it forms an integral part of the forest resource inventory [32–34]. The parameters measurable by the tree-measuring smartphone are currently limited to basic data such as DBH, tree height, and position. In contrast, the LiDAR SLAM method captures raw point cloud data of the site (Figure 14), facilitating more comprehensive data processing later on, such as calculating canopy width, leaf area index, tree modeling, and estimating volume and carbon storage. We used AdQSM software (v1.7.5) [35] to complete point cloud modeling, and the modeling results are shown in Figure 15. The dense point

cloud generated by the LiDAR SLAM scheme supports single-tree modeling and volume measurement, which is a functionality that cannot be achieved with the sparse point clouds generated by visual SLAM. In the future, we expect to use digital twin technology to build a Tree Information Model (TIM) and use it to simulate and solve parameters such as tree growth and biomass. A complete single tree point cloud can provide data support. Overall, regarding adaptability to the forest environment, LiDAR SLAM and visual SLAM each present unique advantages and disadvantages. Therefore, in practical applications, it is advisable to design a reasonable investigation plan tailored to the characteristics of the plot area.

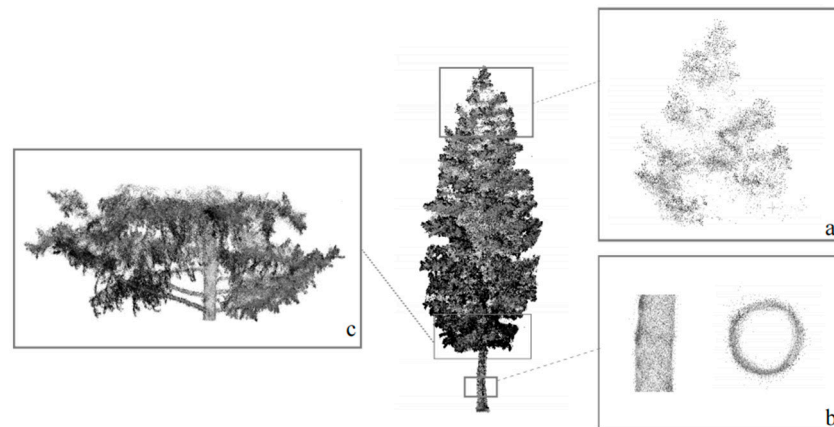


Figure 14. Tree point cloud based on LiDAR SLAM algorithm. (a) Point cloud characteristics at the tree canopy, (b) Point cloud characteristics at DBH of the trunk, and (c) point cloud characteristics of branches and leaves in the undertree layer.

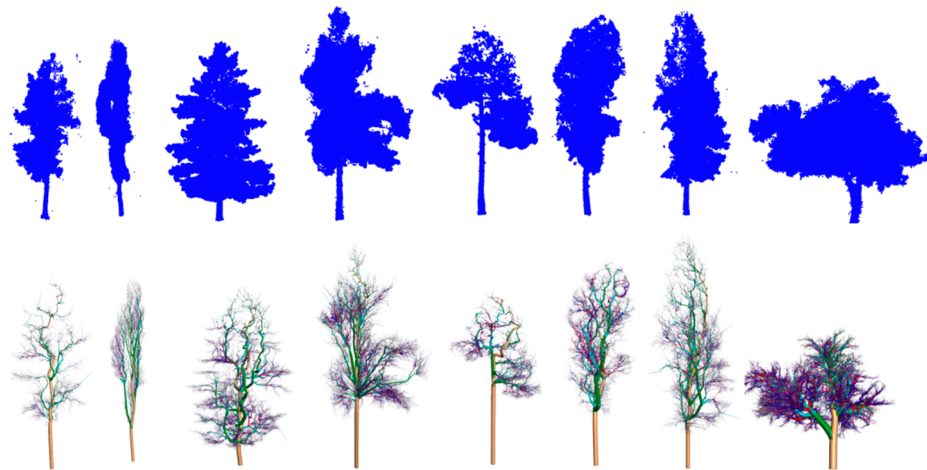


Figure 15. Point cloud modeling effect based on AdQSM.

5.3. Economic Cost

There are significant economic cost differences between visual SLAM, LiDAR SLAM, and traditional forestry plot survey methods (Table 6). First, visual SLAM uses cameras and algorithms for 3D environmental reconstruction, making the equipment cost relatively low, as it mainly relies on cameras and computational resources. However, its accuracy can be affected by lighting conditions, requiring additional labor in complex forest environments to adjust the equipment's position or repeat operations, which increases labor costs. In contrast, LiDAR SLAM offers higher accuracy and better adaptability to various environments, but the price of LiDAR equipment is expensive. Although it reduces the need for repeated fieldwork, the initial investment is significant, and the maintenance costs are high. Traditional forestry plot survey methods have simple equipment and low costs but require

extensive labor and time, especially in large forest areas, where survey efficiency is low. In the long run, labor costs become high. Overall, visual SLAM is more cost-effective for small-scale applications, while LiDAR SLAM is advantageous for high-precision requirements and large-scale applications. Traditional methods are suitable for low-budget projects with abundant labor resources. We believe that the LiDAR SLAM-based scheme is better suited for larger forestry operation areas and higher plot survey demands, while Visual SLAM devices are more suitable as intelligent measurement tools to replace traditional equipment, enhancing efficiency for small-scale surveys with lower data requirements.

Table 6. Economic cost of each method.

	Equipment Cost	Labor Cost	Time Cost
Traditional methods	low	high	high
VSLAM	medium	low	medium
LSLAM	high	low	low

5.4. Limitations and Prospects

Following our experimental testing, both the handheld laser scanner based on LiDAR SLAM and the tree-measuring smartphone based on visual SLAM have demonstrated their advancement and accuracy in forest plot surveys, significantly enhancing the efficiency of such surveys. However, this study was constrained by a limited number of plots, exclusively comprising plantation plots, and did not encompass a broad spectrum of forest environments, notably lacking tests in areas with complex forest conditions. Additionally, our comparison of parameters was restricted; we solely assessed the accuracy of three main parameters: diameter at breast height (DBH), position, and tree height, while other potential forest survey data were not considered in this study. Furthermore, there are still many factors affecting the accuracy of parameter estimation. For example, when using LiDAR to survey the plot, factors such as different survey routes and forest structures can affect the scanning effect [4,29]. Additionally, in parameter estimation, different circular fitting methods can also have an impact [36].

Looking forward, forestry professionals can continue to evaluate the differences between various survey methods in forestry work, discern the strengths and weaknesses of each method, and persist in refining SLAM algorithms for forestry applications. By doing so, they can improve survey methods and further enhance the efficiency and quality of forest resource surveys.

6. Conclusions

This study compared the accuracy and suitability of two forest plot survey methods based on SLAM through experimental testing. The results showed that the tree measurement accuracy of the tree survey smartphone based on visual SLAM was superior to that of the LiDAR SLAM algorithm, with errors controlled within 1 cm. In terms of the accuracy of tree position and height, both survey methods performed similarly, achieving good survey results. In terms of suitability for forest environments, the equipment based on the LiDAR SLAM algorithm could efficiently and conveniently complete field surveys, but its effectiveness could be affected by tree density and height in the plot, especially in densely populated plots where occlusion may occur. In comparison, the tree survey smartphone based on visual SLAM could complete data processing and recording during data collection with less post-processing work, but it may be constrained by the complex forest environment during data collection, and the parameters obtained are limited. Therefore, the advantages and disadvantages of the two methods are apparent, and forestry workers should choose the survey method reasonably according to the characteristics of the plot environment and survey requirements.

Author Contributions: Methodology, Y.W.; Software, P.Z. and R.W.; Data curation, Y.S.; Writing—original draft, T.G.; Funding acquisition, F.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by National Key R&D Program of China, grant number [2023YFF1304305] and Tibet Autonomous Region Science and Technology Plan Project, grant number [XZ202301YD0043C].

Data Availability Statement: Data are contained within the article.

Conflicts of Interest: The authors declare no conflicts of interest.

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