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A Data Processing Framework for Evaluating Smartphone LiDAR Accuracy and Point Cloud Correspondence

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Modern smartphones have evolved beyond their original function as communication tools to serve as versatile digital assistants. In this study, we evaluate and compare the 3D scanning accuracy of light detection and ranging (LiDAR) sensors embedded in various smartphone models under diverse real-world conditions. To replicate real-world conditions, scanning experiments were conducted across different distances, lighting environments, and surface materials. The exported 3D models were subsequently analyzed using SolidWorks to quantify geometric deviations from the corresponding physical objects. Throughout the study, it was observed that the absolute error across all measured directions remained below 1.1 mm, while the relative error did not exceed 2.12%. These results indicate that smartphone LiDAR systems are capable of satisfying the accuracy demands for typical use cases such as dimensional assessment and 3D reconstruction.

1. Introduction

Light detection and ranging (LiDAR) technology, which utilizes laser pulses to perform distance measurements for three-dimensional spatial perception, has been increasingly adopted in a wide range of applications in recent years, including topographic surveying, architectural modeling, autonomous vehicles, and augmented reality (AR). Amid the growing adoption of digital twin systems, virtual reality (VR), and intelligent building technologies, there is a rapidly increasing demand for methods capable of acquiring precise spatial and geometric data in an efficient and cost-effective manner. Because of their ubiquity and portability, smartphones hold great potential as accessible tools for daily 3D spatial sensing. Despite continuous advancements in computational power and sensor integration, the embedded LiDAR modules in smartphones

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still demonstrate considerable disparities in accuracy, reliability, and adaptability to environmental conditions compared with high-end, professional-grade LiDAR systems.

In recent studies, researchers have attempted to bridge this technological gap between industrial-grade systems and portable sensing platforms. Recent advancements in urban-scale 3D digitization have demonstrated the effectiveness of mobile LiDAR platforms for seamless point cloud integration and surface reconstruction.[1] For example, vision-based sensing systems have been successfully applied in urban traffic scenarios such as lane departure detection,[2] highlighting the relevance of spatial sensing technologies in mobility-related applications. A smartphone-based method for estimating tree diameter at breast height (DBH) was proposed, which avoids the need for physical measurement tools like calipers or tape, by side-view imaging and automated image analysis, showing the promise of lightweight, image-based 3D estimation techniques in forestry.[3] In the agricultural domain,[4] terrestrial LiDAR systems have been applied to measure microtopography in farmlands, enabling the high-resolution reconstruction of soil surface features such as furrows and depressions, which are critical for assessing water flow and erosion risk.

In animal science,[5] researchers have demonstrated that smartphones can be used to estimate the body weight of pigs through side-view imaging and regression models, achieving high accuracy and offering an intelligent, noninvasive solution for livestock monitoring. Similarly, in civil and structural engineering,[6] an adaptive scan planning algorithm was developed to enhance terrestrial laser scanning in complex 3D environments by dynamically optimizing scanner placement on the basis of occlusion and visibility, thus ensuring complete and efficient coverage. In addition, machine learning has been effectively applied to identify nonlinear behaviors in robotic systems, which suggests its applicability in modeling deviations in LiDAR-based spatial sensing under complex environmental conditions.[7]

While these applications show great potential, the challenge of data fidelity and resolution remains. Notably,[8] high-precision soil surface reconstruction using terrestrial LiDAR has proven more effective than traditional pin profilers in capturing soil morphology after tillage, highlighting LiDAR’s advantage in capturing subtle vertical variations. However, data post-processing can introduce distortions[9]—one study revealed that interpolating LiDAR point clouds into digital elevation models (DEMs) leads to a systematic underestimation of surface roughness by 7–20%, particularly on rough terrain, underscoring the importance of using raw point cloud data for accurate temporal monitoring.

From a biological perspective,[10] the accuracy of tree biomass estimation has been linked to genetic variation in growth patterns, suggesting that integrating spatial LiDAR data with genotype-based modeling can enhance forest carbon stock assessments. Furthermore,[11] the feasibility of using smartphone accelerometers for modal analysis in structural health monitoring has been validated, offering a portable alternative for identifying natural frequencies in bridges or buildings. Beyond natural systems, LiDAR has also proven effective in infrastructure inspection. For example,[12] terrestrial LiDAR scans of asphalt surfaces have been used to generate 3D point clouds, DEMs, and hill shade maps for the identification of 15 pavement distress types. This research showed that hill shade maps are particularly useful for visualizing subtle surface deformities, while high-resolution point clouds achieved centimeter-level accuracy in damage quantification.

Despite these advancements, most existing research continues to focus on industrial-grade LiDAR systems, leaving a gap in comprehensive validation frameworks for smartphone-based 3D sensing. In this study, we address that gap by developing a multidimensional testing protocol to systematically evaluate the performance of smartphone-embedded LiDAR sensors under varying environmental conditions—including lighting intensity, surface material, and measurement distance. Our framework integrates geometric accuracy assessment, controlled illumination simulation, and graphical error mapping, with validation performed through absolute error (AE) analysis, root mean square error ($RMSE$), and paired t-tests. We hope that our findings will contribute to the future design and application of portable 3D sensing systems in both scientific and everyday contexts.

2. Materials and Methods

To evaluate the measurement accuracy and environmental adaptability of various 3D scanning devices, we designed a structured experimental workflow composed of four key stages: device setup, 3D model construction, geometric data acquisition and comparison, and error analysis. In the device setup stage, three smartphone models equipped with embedded LiDAR sensors (Models A, B, and C) and two commercial-grade 3D scanners (Scanners A and B) were selected. Each device scanned the same metallic object using their respective native or proprietary applications. In the second stage, 3D models obtained from the smartphones were exported in Universal Scene Description Zipped (USDZ) format and converted into STereoLithography (STL) files via an online tool. In contrast, the scanner-derived models were directly exported as STL files. All models were then imported into SolidWorks 2022, where unit normalization and coordinate alignment were performed.[13] For the geometric comparison stage, physical dimensions—length, width, and height—were measured using a Mitutoyo 530-312 vernier caliper with an accuracy of ±0.02 mm and served as the ground truth. These measurements were compared with the corresponding dimensions extracted from the digital models using the SolidWorks measurement tool. Finally, the error analysis module employed multiple evaluation metrics including AE, relative error (RE), $RMSE$, and the coefficient of determination (R^2). RE was computed as

$$RE = \frac{\left|V_{measured} - V_{reference}\right|}{V_{reference}} \times 100\%. \tag{1}$$

This process enabled comprehensive the quantification of geometric deviations between digital and physical measurements, providing insights into device performance under various scanning conditions. Sensitivity analysis methods such as Sobol and FAST were previously applied to LiDAR-camera calibration to quantify uncertainty propagation in 3D reconstruction workflows.[14]

To comprehensively evaluate the measurement accuracy and stability of different types of scanning devices in the 3D modeling process, we designed a multidevice comparative experimental procedure. The evaluation included three smartphone models equipped with

LiDAR sensors (Smartphones A, B, and C), as well as two non-smartphone 3D scanners (Scanners A and B). All devices were employed to scan the same target object and their 3D models were compared against physical measurements for error analysis. The test object was a metallic pentagonal workpiece made of carbon steel. Measurements were taken for its length, width, and height. The smartphone group utilized built-in 3D scanning applications to conduct an orbiting capture process (approximately 75 to 100 images per scan), generating models in USDZ format, which were then converted to STL files using the online tool imagetostl.com. Scanners A and B completed the 3D scanning tasks using their respective proprietary software and default parameter settings, and also exported the models in unified STL format.

To ensure consistency across experiments, all scans were conducted at a fixed distance of 30 ± 2 cm. Two lighting conditions were applied: a bright environment (with 4000K and 6500K LED lighting) and a dark environment (without natural light sources), as shown in Fig. 1. Each device performed five repeated scans to ensure data stability. The resulting 3D models were imported into SolidWorks 2022, and the "Measurement" function was used to extract geometric data along the *X*-, *Y*-, and *Z*-axes. The physical dimensions obtained using a Mitutoyo 530-312 caliper (accuracy ±0.02 mm) were used as the ground truth reference. The evaluation metrics included *AE*, *RE*, *RMSE*, and R^2 to assess measurement accuracy across different dimensions. In addition, a paired t-test was conducted to examine whether there were statistically significant differences between scanned values and actual measurements. Visualization methods such as error bar and box plots were employed to illustrate the stability and error distribution trends of each device.

3. Results and Discussion

In this study, the measurement accuracies of LiDAR sensors integrated into Smartphones A, B, and C were compared through 3D scanning experiments, and the results were analyzed against reference physical measurements. The experimental findings showed that *AE* for length measurement was 0.86 mm, with *RE* of 0.862%; for width, *AE* was 1.02 mm (*RE*: 2.05%); and for

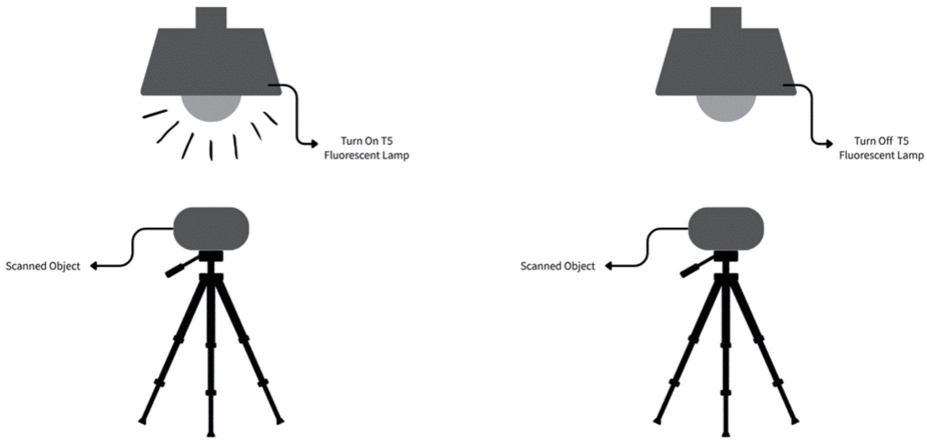

Fig. 1. Schematic diagram of LiDAR experiment.

height, *AE* was 1.04 mm (*RE*: 1.041%). All *AE*s across the three dimensions were below 1.1 mm, and all *RE*s were within 2.1%, demonstrating that smartphone-integrated LiDAR modules provide a high level of spatial measurement accuracy sufficient for dimensional evaluation and 3D modeling tasks in general use scenarios. Noncontact visual measurement techniques, such as machine-vision-based gap detection, have demonstrated high repeatability and are consistent with the use of smartphone LiDAR for surface geometry estimation under varying conditions.(15) Reflective components within LiDAR systems have also been optimized via selective laser melting, providing structural advantages in compact sensor design.(16)

It was observed that measurements on the lateral plane were more susceptible to deviations, likely owing to variations in user grip and the effect of surface materials, which affected the resolution consistency and caused certain values to deviate from the central trend. Nevertheless, the overall error range remained within practically acceptable limits. Particularly in applications such as rapid modeling and preliminary spatial estimation, smartphone LiDAR systems exhibit significant potential as a low-cost and accessible alternative to professional 3D scanning solutions.

Table 1 presents the dimensional measurements (length, width, and height) of a pentagonal metallic object acquired by each scanning device under two environmental conditions: bright and dark room conditions. The results show the following trends:

- The three smartphones (Phones A, B, and C) produced consistent measurements across both lighting conditions, with relatively small variations.
- Scanner A yielded notably higher values, especially in the height dimension, reaching 108.566 mm under dark room conditions. This may suggest sensitivity to surface reflections or ambient lighting fluctuations.
- Scanner B provided stable results in both environments, with moderate variation compared with the results of smartphones and Scanner A.

These measured values form the basis for the subsequent calculation of *RE*, which is further visualized and discussed in the following figures.

Figure 2 shows the *RE* values for three smartphones (red box), Scanner A (yellow box, two trials), and Scanner B (green box, two trials) in a well-lit environment. Each data point represents *RE* in one of the three measured dimensions (length, width, or height). The chart provides a visual comparison of measurement accuracy and consistency among the different devices under identical lighting conditions.

Figure 3 illustrates the *RE* values for three smartphones (red box), Scanner A (yellow box, two trials), and Scanner B (green box, two trials) under low-light (dark room) conditions. Each

Table 1
Dimensional measurements under different lighting conditions.

	Bright room			Dark room		
	Length (mm)	Width (mm)	Height (mm)	Length (mm)	Width (mm)	Height (mm)
Phone A	102.390	51.844	100.798	101.550	51.002	100.009
Phone B	100.699	50.550	102.114	100.505	49.453	99.632
Phone C	100.126	50.705	101.135	100.890	50.704	101.059
Scanner A	110.198	56.590	103.344	105.766	48.334	108.566
Scanner B	101.738	52.352	102.070	101.202	53.344	103.008

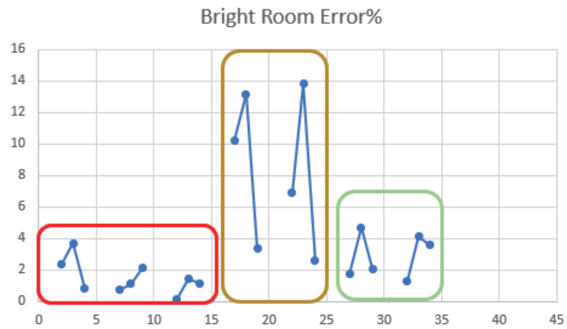

Fig. 2. (Color online) Distribution of *RE* values (%) for each scanning device under bright room conditions.

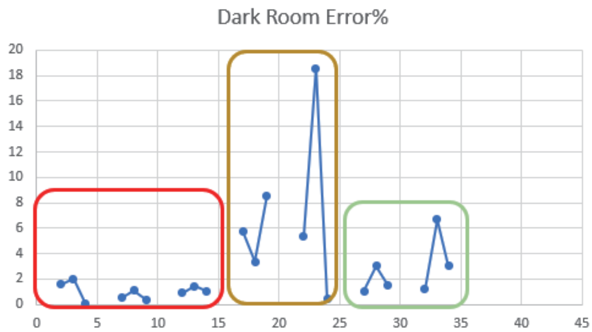

Fig. 3. (Color online) Distribution of *RE* values (%) for each scanning device under dark room conditions.

data point represents *RE* in one of the three measured dimensions (length, width, or height). The figure highlights the impact of reduced lighting on the measurement accuracy and stability of each device.

4. Conclusions

By comparing the measurement performance of LiDAR sensors embedded in smartphones for 3D scanning applications, we demonstrated that such sensors are capable of fulfilling the demands of dimensional assessment and modeling in typical environments. Supplementary experiments involving static object scanning under different lighting conditions (bright and dark environments) revealed that smartphones exhibited measurement errors of less than 2% in length and height estimations, with some cases achieving errors as low as 0.01%, indicating excellent stability and reliability. While measurements along the width axis were slightly affected by lateral reflections and variations in holding angles, leading to slightly increased errors, the overall accuracy remained within acceptable limits, validating the feasibility of employing smartphones as practical tools for everyday spatial perception.

Furthermore, with the aid of error visualization and statistical analysis, we established a reproducible validation framework and explored the potential of extending smartphone LiDAR applications to dynamic measurements and complex environments, including nonrigid objects and mobile scanning scenarios. In conclusion, although smartphone-based LiDAR systems exhibit certain limitations in resolution and stability compared with industrial-grade devices, they offer significant advantages in portability, cost-efficiency, and real-time performance, making them viable tools for general-purpose 3D scanning. These strengths provide practical value in domains such as industrial design, BIM, and human factors engineering, and position it as a promising solution for affordable 3D scanning and data acquisition in the future.

The results of this study confirm the applicability of smartphone-embedded LiDAR sensors in dimensional measurement and 3D modeling; however, several technical limitations remain. Measurement accuracy is highly sensitive to user handling stability, surface reflectivity, and ambient lighting conditions, which potentially lead to deviations. Moreover, the experiments were conducted primarily on rigid and static objects, leaving the performance in nonrigid or dynamic scenarios unexplored. Future research could incorporate deep learning algorithms for error compensation, multisensor fusion, and automated calibration techniques to enhance accuracy and robustness under diverse environmental conditions.(17) Future developments in hybrid point cloud analysis may benefit from dynamic logic-based clustering frameworks, as shown in recent advances in object recognition and semantic segmentation.(18) The integration of deep-learning-based defect identification frameworks may inspire similar architectures for dynamic scene interpretation in smartphone LiDAR systems.(19,20)

In terms of practical applications, smartphone-based LiDAR systems offer significant advantages in portability and accessibility, making them suitable for a wide range of domains. In building information modeling (BIM),(21) they can support on-site inspection and spatial updates. In agricultural monitoring, they can facilitate crop height scanning and morphological analysis, contributing to yield prediction and pest assessment. In the medical and rehabilitation fields, these systems can enable posture analysis and motion evaluation, offering a low-cost and noninvasive solution for home-based care. Additionally, in cultural heritage preservation, smartphone LiDAR provides a convenient and minimally invasive tool for real-time 3D documentation and digital archiving. These cases of use highlight the broad potential and developmental space of portable and efficient 3D scanning technologies in the context of smart environments.

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