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Evaluating the accuracy and quality of an iPad Pro's built-in lidar for 3D indoor mapping

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ABSTRACT

This study aimed to assess the accuracy of the lidar sensor on an iPad Pro and its potential for creating 3D BIM. Data was collected through different scanning methods in various environmental conditions. The results showed that the iPad Pro's lidar sensor produced accurate point clouds in static acquisition experiments with point distances of less than 1 mm from their best-fitting plane. However, in dynamic acquisition experiments, the distance increased to an average of 1 cm due to changes in the iPad Pro's pose. The study also found that the accuracy of the registered point clouds was better when scanning smaller areas with limited pose changes. Based on the findings, the study recommends maintaining a distance of 1–1.5 m between the iPad Pro and the target, as the target's color has minimal impact on scanning accuracy. Avoiding large posture changes while scanning can improve the accuracy of the point clouds in scan-to-BIM projects.

1. Introduction

1.1. Motivation

Building information modeling (BIM) is a digital collaboration tool widely used in building construction and management (Eastman et al., 2011). This technology allows civil engineers, architects, and related partners to collaborate efficiently. However, BIM analysis cannot be directly applied to existing or historical buildings due to the absence of a 3D building information model. To address this issue, Rocha and Mateus (2021) proposed the scan-to-BIM technology, which reconstructs a 3D BIM from 3D point clouds using laser scanners. The quality and density of the point clouds significantly impact the accuracy of building shape in the scan-to-BIM process (Teo and Chen, 2007; Rebolj et al., 2017; Wang et al., 2022b). Thus, ensuring the quality of point clouds is critical for 3D building modeling.

In recent years, low-cost laser scanners, e.g., the Apple iPad's lidar, have gained increasing popularity among consumers. These mobile or handheld devices typically integrate multiple sensors to improve their 3D scanning capabilities. While consumer-grade laser scanners may not match the accuracy of survey-grade professional scanners, they offer the advantage of capturing 3D geometrical information directly and efficiently (Haenel et al., 2022). Consequently, low-cost laser scanners hold great potential for indoor building modeling.

1.2. Previous studies

Wang et al. (2019) proposed a four-step framework for implementing scan-to-BIM. The framework involves: (1) listing information about the building elements, (2) selecting an appropriate laser scanner, (3) capturing point clouds by scanning the area, and (4) reconstructing the BIM from 3D point clouds. Romero-Jarén and Arranz (2021) evaluated two point clouds acquired via static and dynamic laser scanning techniques. Point cloud quality plays a crucial role in identifying building elements accurately. Rebolj et al. (2017) proposed several point cloud quality parameters (e.g., point density, accuracy, and coverage) to ensure the quality of scan-to-BIM applications. The experimental results showed that these parameters can be used as comparable indices between point clouds and the existing BIM.

Due to the low-cost and ease-to-use, consumer-grade laser scanners are popular and cost-effective tools to acquire terrestrial 3D data. Several low-cost consumer-grade laser scanners are available, e.g., Google Tango, Microsoft Kinect series, and Apple lidars. Google Tango uses multi-sensor integration and the simultaneous localization and mapping (SLAM) technique on a mobile platform, and its depth sensor can reach up to 4 m. It can be used for augmented reality, indoor measurements, indoor positioning, and other indoor applications (Gradmann et al., 2018; Gülch, 2016; Nguyen and Luo, 2017). The Microsoft Kinect series has three versions: Kinect v1, Kinect v2, and

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Azure Kinect. Azure Kinect has a distance error of less than 11 mm when the distance between sensor and object is over 3.5 m. Both Kinect v1 and v2 have one depth camera and one color camera. Kinect v1 measures depth with the pattern projection principle, while Kinect v2 and Azure Kinect use the continuous wave intensity modulation approach to obtain depth information (Tölgyessy et al., 2021). Other consumer-grade lidar sensors are the Apple iPad Pro and iPhone Pro (Hallereau et al., 2020; Luetzenburg et al., 2021). The Apple lidar module use a consumer-grade direct time-of-flight (dToF) for depth sensing and a vertical-cavity surface-emitting laser (VCSEL) lidar system as the 3D sensor module.

Several studies have evaluated the performance of Microsoft Kinect from different perspectives. Khoshelham (2012) compared the depth data obtained from Kinect via a mathematical geometry model with experimental data and found a random error of 4 cm. Hämmerle et al. (2014) compared the Kinect and terrestrial lidar on capturing natural karst cave 3D object. The experimental results showed that the Kinect was suitable for capturing flowstone walls and deriving morphometric parameters, but there are differences s (mean of 1 mm with 7 mm standard deviation) with lidar measurements on strongly varying and curved surfaces. Sabale and Vaidya (2016) reported an absolute mean percentage error of about 3.6% between the measured depth and true depth. Lachat et al. (2015) identified five main factors that affect scanning accuracy, including the number of depth frames, the preheat time of the sensor, the color of the target, the influence of sunlight, and the distance between the sensor and the target.

During the past couple of years, there has been an increase in the number of mobile mapping applications incorporating Apple's lidar sensor for acquiring 3D data. For the accuracy and quality assessments of 3D measurements, Chase et al. (2022) used the Modelar 3D scanning App and compared the tool's efficacy to terrestrial laser scanning (TLS) used for surveying. The Modelar app achieved absolute accuracies of $\pm$3 cm horizontally and $\pm$7 mm vertically and a relative accuracy of $\pm$3 cm. The study was conducted at a sub-centimeter geometrical accuracy to obtain the 3D measurements. Spreafico et al. (2021) conducted an experiment using the SiteScape App with two scanning methods (static and dynamic). They obtained between 560 and 16,382 points on a flat surface and a distance of less than 1 cm in dynamic acquisition between the points and their best-fitting plane. Additionally, Luetzenburg et al. (2021) utilized an iPad Pro's lidar to scan a coastal cliff in Denmark and achieved an absolute accuracy of about 1 cm for target lengths larger than 10 cm, with a point cloud of high resolution.

For forest applications, Wang et al. (2021) evaluated the efficacy of the lidar sensor of the iPad Pro 2020 for measuring the diameter at breast height (DBH) of urban trees. They used 3D Scanner App to establish 12 combinations of methods and settings for scanning the trees. The method with 10 mm resolution, high confidence, and multiple-tree mode achieved a detection rate of 97%. The highest accuracy estimated for the DBH was 7.52% of the relative root mean square error (RMSE) for multiple-tree mode and 7.27% for single-tree mode. The low confidence setting resulted in significantly higher accuracy of DBH estimation than the high confidence setting. Additionally, the single-tree mode revealed a significantly higher accuracy for DBH estimation than the multiple-tree mode. Wang et al. (2022a) also explored the feasibility of using an iPad Pro's lidar to measure the trees' DBH. The coefficient of determination between the estimated DBH and field measurements was 0.52, indicating moderate accuracy. The RMSE of DBH estimation ranged from 2.82 cm to 8.24 cm. The accuracy of a smaller tree was higher than that of a larger tree. However, the distance between the sensor and the target did not have a significant effect on accuracy. Gollob et al. (2021) also performed an accuracy evaluation and compared the performance of an iPad Pro's lidar and the GeoSLAM ZEB Horizon personal laser scanner in forest investment. The results showed that the detection rate of the iPad Pro's lidar was 97.3%, with an RMSE of 3.13 cm and an operation time of 7.51 min, while GeoSLAM achieved a detection rate of 99.5%, with an RMSE of 1.59 cm and an operation time of 3.75 min.

For cultural heritage applications, Teppati Losè et al. (2022) compared three iOS applications (SiteScape, EveryPoint, and 3D Scanner Apps) for Apple's lidar sensor. Various surveying scenarios for cultural heritage were taken into consideration, including the sensor's overall accuracy, the most effective acquisition strategies, operational constraints, and the 3D positional accuracy of the resulting products. SiteScape permitted the acquisition of a higher number of points than 3D Scanner App and EveryPoint, while 3D Scanner App produced less noisy point clouds by not increasing the number of points upon scanning the same area. Moreover, the experiments indicated that the lidar sensor was not significantly affected by illumination or the material. In addition to the study conducted by Vacca (2023), which evaluated the potential of Apple's lidar sensor for producing precise 3D models of cultural heritage applications, four Apps (i.e., Polycam, SiteScape, 3D Scanner, and Scaniverse) were tested for five case studies related to architectural-cultural heritage assets. Shape complexity was identified as the primary factor influencing the results. The experimental findings suggest that Apple's lidar sensor can be utilized to generate 3D models suitable for metric documentation. It can also be applied to architectural and cultural heritage assets that are not excessively complex in form and texture. Balado et al. (2022) conducted a comparison of three lidar devices (i.e., Faro X330, Zeb-Go, and iPad Pro) in heritage documentation. The point cloud obtained from Faro X330 was the only one that produced satisfactory results for individualizing stones. Conversely, the acquisitions from Zeb-Go and iPad Pro proved to be a rapid solution for obtaining complete models with a lower level of detail.

For indoor application, Díaz-Vilariño et al. (2022) used an iPad Pro's lidar to perform 3D modeling in two consecutive rooms. The local precision was evaluated by analyzing the planar segments extracted from the walls and resulted in an accuracy of 5.3 mm. The global correctness was evaluated by comparing the accuracy results of the iPad Pro's lidar with that of the TLS data and a 3D model, and most of the iPad points were less than 10 cm away from the TLS points and 3D model surfaces. However, larger dimensional errors were observed in parts of the ceiling and a wall due to the process of point cloud creation and incomplete acquisition planning. Thus, special attention should be given to acquisition planning to avoid complex trajectories. Despite these limitations, good color registration was observed in the data, and the iPad Pro showed great potential for 3D indoor mapping toward 3D reconstruction in small environments.

1.3. Need for further study and research purpose

An iPad Pro's lidar shows great potential in BIM applications. Its lidar sensor can be used to reconstruct 3D mesh models for indoor environments. However, most studies have used such lidars for 3D metric surveys or forest mapping. The lidar's application in scan-to-BIM has been relatively less discussed. Therefore, it is important to understand the accuracy of an iPad Pro's lidar for scan-to-BIM applications.

1.4. Objectives

This study aimed to evaluate the accuracy of an iPad Pro's lidar in indoor mapping for scan-to-BIM applications. To achieve this, various experiments were conducted, including static and dynamic acquisitions, and the influencing factors were systematically listed and discussed. The most significant factor was identified, and a practical scan-to-BIM application using the iPad Pro's lidar was performed for evaluation. The accuracy of the point clouds was also evaluated, and the conditions that may affect the results during data acquisition were discussed. Overall, this study provides valuable insights into the use of an iPad Pro's lidar for scan-to-BIM applications.

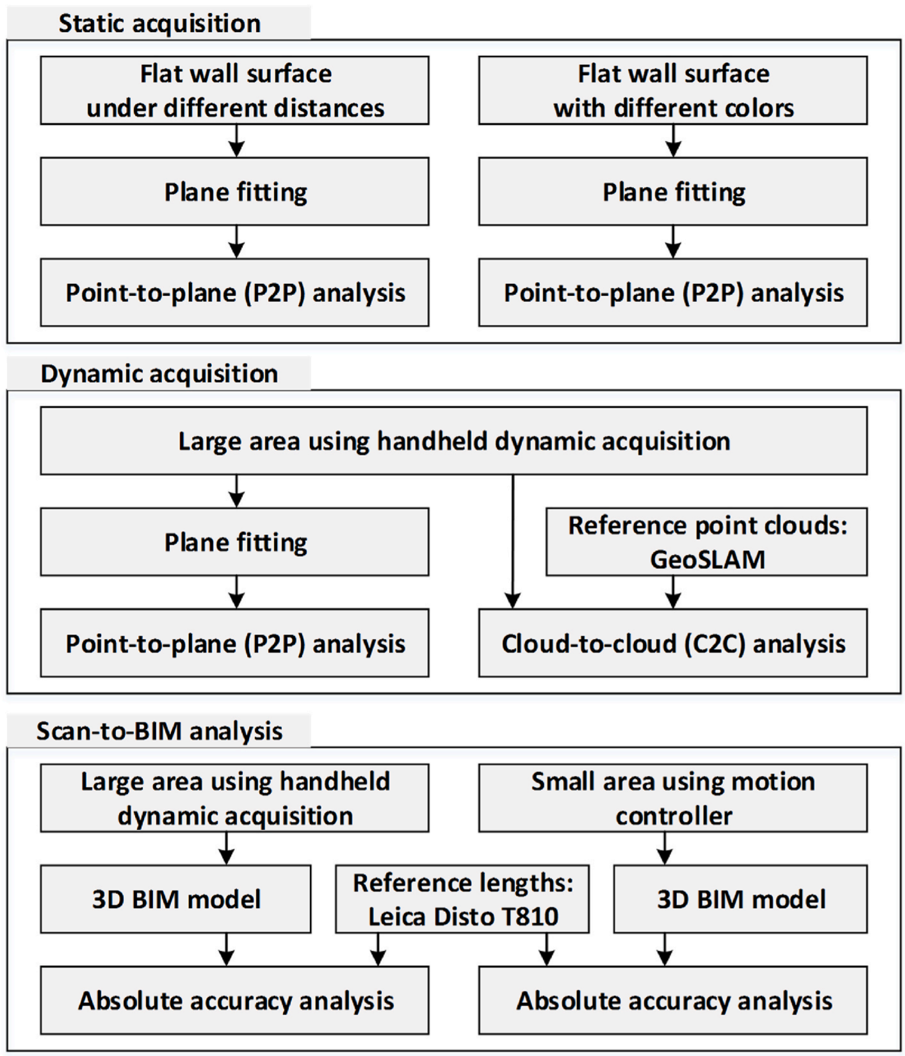


Fig. 1. Workflow of the proposed methods.

2. Methodology

2.1. Instrumentations and tools

This paper presents a study on the use of an Apple iPad Pro's lidar as a low-cost consumer-grade lidar. The lidar sensor is based on the dTOF technology, where a laser with a near-infrared spectrum is emitted by a VCSEL with a 2D array appearance. 3x3 grids, each containing 8x8 points, were emitted using its flash illumination feature. The lidar sensor captured 576 points (=3x3x8x8) in each frame by combining the VCSEL and the single-photon avalanche photodiode. The focal length of the lidar sensor was 26 mm, and the maximum scanning distance was 5 m. More details can be retrieved by referring to Luetzenburg et al. (2021).

To evaluate the accuracy of the iPad Pro's lidar sensor, reference data were collected using the Leica Disto D810 ranger, the GeoSLAM ZEB Horizon scanner and TLS Leica RTC360. Leica Disto D810 was used for distance measurement, with a range accuracy of 1 mm and a measuring range from 0.05 m to 200 m. The GeoSLAM ZEB Horizon included the Velodyne VLP-16 scanner, and 300,000 points were gained per second. The maximum range distance was 100 m, and the relative accuracy was about 6 mm. The terrestrial laser scanning Leica RTC360 has an accuracy of 1.9 mm at 10 m distance. The maximum range distance was 130 m. The angular and range accuracies were 18″ and 1.0 mm + 10 ppm, respectively.

Two applications, 3D Scanner and RTAB-Map Apps, were used to obtain the point clouds using the iPad Pro in this study. 3D Scanner App was used to obtain a color mesh model, where the lidar, camera, and inertial measurement unit worked together while scanning. The raw points were triangulated together to generate a mesh model using the ARKit, and the outputted point clouds were resampled from the mesh model (Luetzenburg et al., 2021). As 3D Scanner App provided high-density points, it was used in a static acquisition experiment. The second application, the RTAB-Map app, was used in the dynamic acquisition experiment. RTAB-Map is an open-source lidar and visual SLAM library for large-scale and long-term online operations (Labbé and Michaud, 2019). When this process recognizes the same location visually, the map is optimized with the loop closure constraints. Therefore, we used the RTAB-Map app in the dynamic acquisition experiment.

2.2. Methodologies

The purpose of this study was to assess the accuracy of an iPad Pro's lidar in 3D indoor mapping. The proposed scheme comprises three major parts, as depicted in Fig. 1: (1) accuracy analysis of static acquisition by a tripod; (2) accuracy analysis of dynamic acquisition by SLAM; and (3) accuracy analysis of the reconstructed 3D BIM model.

2.2.1. Accuracy analysis of static acquisition

In this study, two different scenarios were designed to analyze the static acquisition accuracy of an iPad Pro. Static acquisition was per-

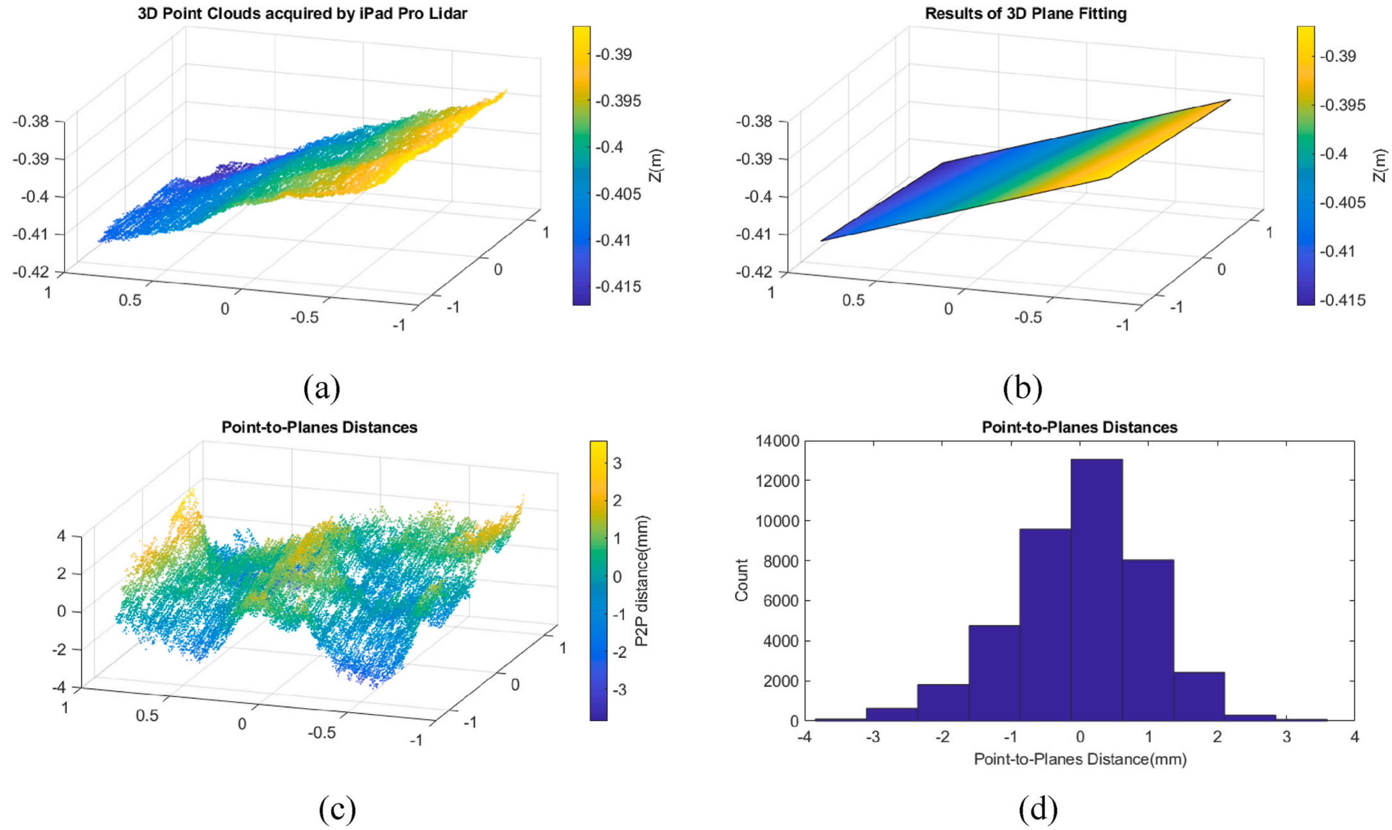


Fig. 2. Distance analysis between the points and their best-fitting plane: (a) 3D point clouds acquired by iPad Pro Lidar; (b) the calculated best-fitting plane; (c) calculation of the point-to-plane distance for each point; (d) a histogram showing the distribution of P2P distance errors.

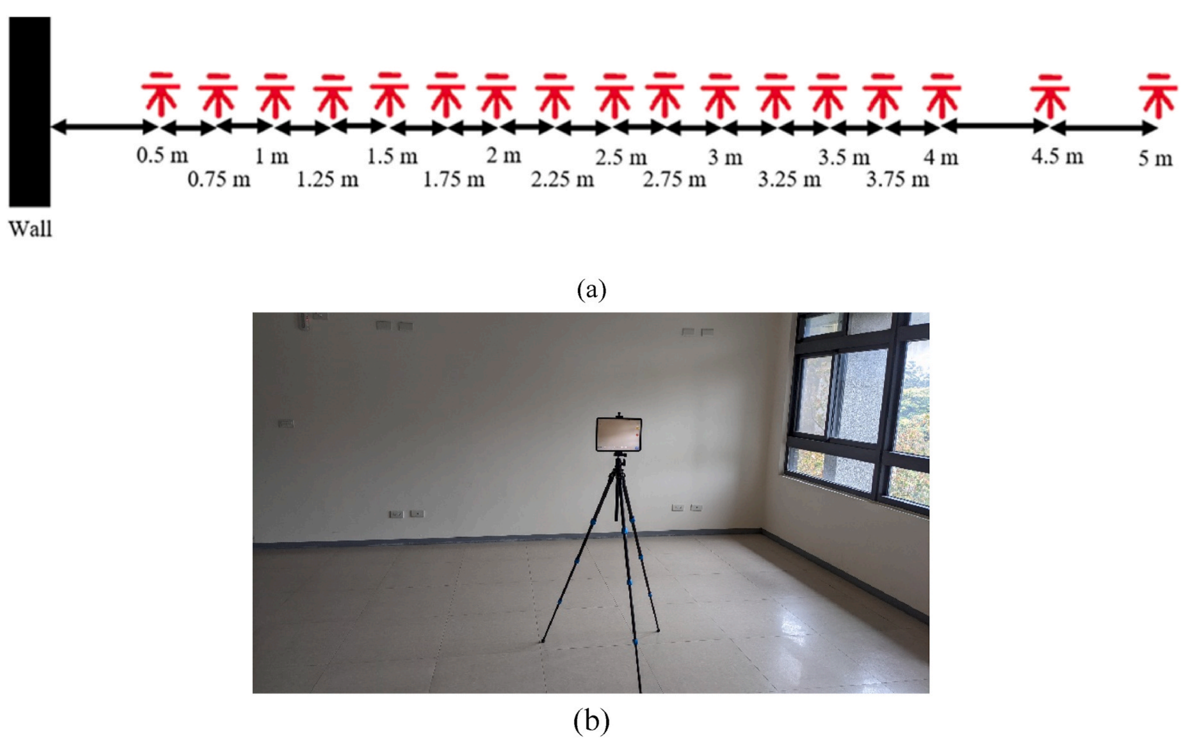


Fig. 3. Configuration of distance analysis in static acquisition: (a) instrument setup at different distances from the target; (b) experiment field and instruments used in the study.

(b) (b)

Fig. 4. Configuration of the target's color analysis: (a) setup of the instrument; (b) nine colors used in this experiment. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

formed by fixing the iPad Pro on a tripod, and the target was a planar object. The first scenario examined the relationship between the depth distance and the accuracy of the iPad Pro, while the second scenario investigated the relationship between the target's color and the iPad Pro's accuracy. The analysis involved analyzing the relative accuracy using the least squares method to calculate the flatness of the point clouds. The 3D planar equation (Nakagawa et al., 2021) is shown in Equation (1), and the point-to-plane (P2P) distances (Equation (2)) were obtained to calculate the mean and standard deviation error. A 1 mm distance threshold was set, and the ratio of the points meeting the 1 mm criteria was calculated. Fig. 2 shows the results of calculating the point-to-plane distance from 3D point clouds and a fitted plane. Fig. 2a illustrates the 3D point clouds obtained from an iPad Pro Lidar. These points were utilized to derive a 3D plane (Fig. 2b) utilizing the least-squares adjustment method. Subsequently, the point-to-plane distance (Fig. 2c) for each point was computed utilizing Equation (2). Finally, Fig. 2d depicts the distribution of P2P distances using a histogram.

$$aX+bY+cZ+d=0 \tag{1}$$

$$e=\frac{|aX_p+bY_p+cZ_p+d|}{\sqrt{a^2+b^2+c^2}} \tag{2}$$

where (X,Y,Z) are the coordinates of the point; (a,b,c,d) are the coefficients of the planar equation; and e is the P2P distance.

The scanning target in this experiment was a white wall considered to be a flat surface, and the iPad Pro was fixed on a tripod to scan the surface statically. Fig. 3a depicts the experimental setup. The distance between the wall and the instrument was initially set at 0.5 m, and the instrument was moved to 0.25 m away from the wall to the second position after completing the first scanning task. The depth distances ranged from 0.5 m to 5 m, and each distance was scanned ten times for 30 s. The maximum scanning distance of the iPad Pro was 5 m, and the positions of the instruments were 4.5 and 5 m away from the wall when the distance was over 4 m. The experimental scenarios are illustrated in Fig. 3b.

The iPad Pro's scanner comprised a camera and a flash lidar sensor that operated through near-infrared light. To investigate the effect of the target color on scanning accuracy, this experiment analyzed the relationship between the target's color and the data's accuracy. Eight colors of poster paper (red, orange, yellow, green, blue, indigo, purple, and black) were sequentially pasted on a flat wall, and the iPad Pro was set up at a distance of 1 m from the colored paper. The colored paper and the scanning configuration are presented in Fig. 4. Ten scans were performed on each target, and only the colored area was selected for accuracy analysis.

2.2.2. *Accuracy analysis of dynamic acquisition*

In this study, a dynamic acquisition experiment was conducted in an indoor hallway with a vertical closed-loop path comprising two floors and two stairs. The dimensions of the area were approximately 62 x 9.5 x 4.5 m^3. The scanning task was initiated from the lower floor and proceeded through the stair to the upper floor, returning to the start point again via the second stair (Fig. 5). The iPad Pro was hand-carried throughout the scanning process, and efforts were made to maintain a steady scanning pace. The RTAB-Map App was employed for this task, given its closed-loop detection function that optimizes point clouds.

To evaluate the accuracy of dynamic acquisition, two methods were employed. The first method involved the same analysis technique as that used in the static acquisition experiment. The planar walls and floors were manually segmented, and the statistics of the P2P distances were obtained. Additionally, a 1 cm threshold was set to calculate the ratio of the points meeting the specified criteria. The second method involved comparing the point clouds obtained by the iPad Pro with a higher-accuracy scanner (i.e., the GeoSLAM ZEB Horizon) using the cloud-to-cloud (C2C) analysis function of the open-source software,

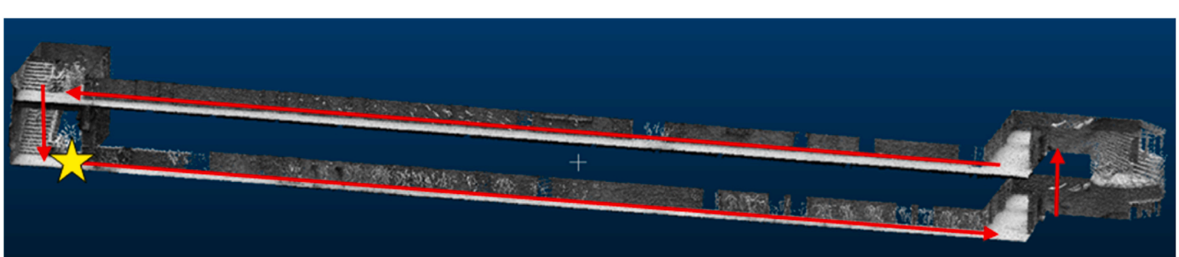


Fig. 5. Experimental area and the scanning path in this task.

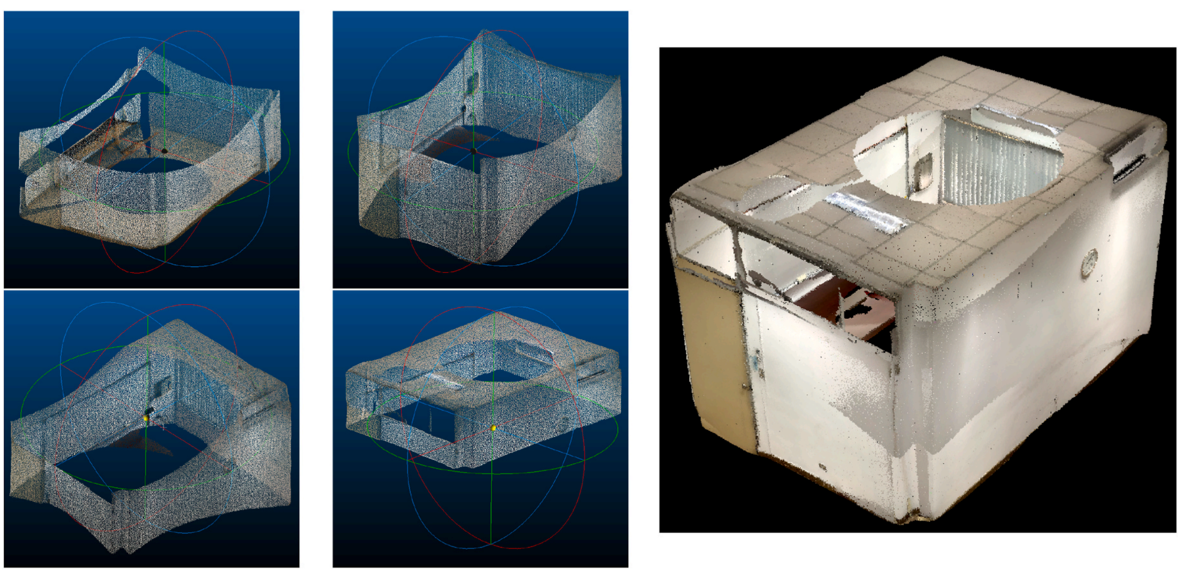
Fig. 6. Motion control device used in the TLS iPad task.

CloudCompare. This function involved registering the two point clouds through an iterative closest point (ICP) algorithm, which calculated the distance between the two point sets. The resulting C2C distances were displayed in different colors according to the distance error. This result also indicated which part of the point clouds contained a higher error.

2.2.3. Accuracy analysis of the reconstructed 3D BIM models

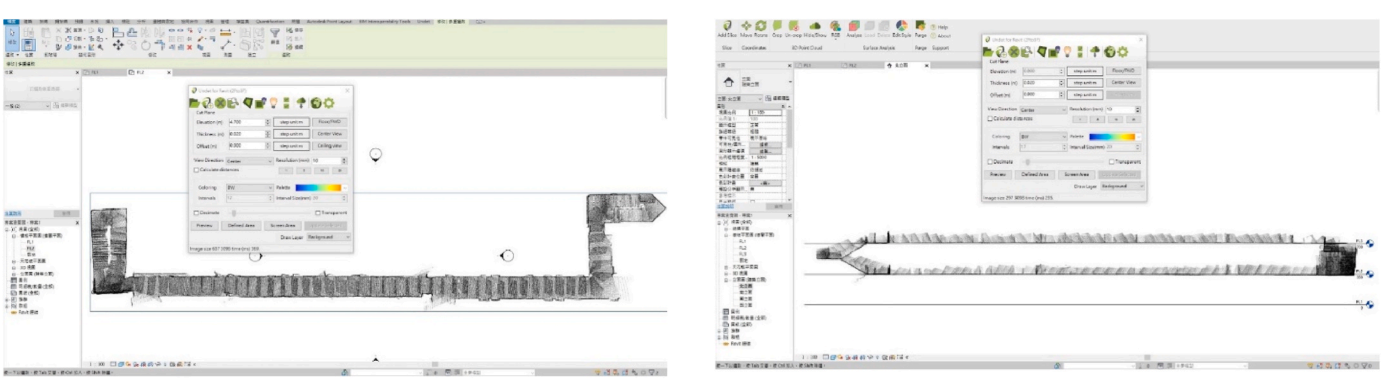
This study conducted a scan-to-BIM workflow in two test areas. The first area was an indoor hallway with a vertical closed-loop path, as described in section 2.2.2. The second area was a meeting room with dimensions of approximately 4.8 x 3.3 x 3.0 m^3. In the dynamic acquisition of the meeting room, an iPad Pro mounted on a motion control device rotated 360° horizontally while scanning (Fig. 6). The working principle of this scanning method is similar to TLS. Therefore, this dynamic scanning can be treated as TLS iPad. The co-registration of TLS iPad data is based on the Lidar-SLAM technique, which matches point clouds between successive scans and registers them into a unified coordinate system. On the other hand, the TLS Leica uses precise angular measurement to merge all profiling scans into a unified coordinate system. The co-registration of TLS iPad stations relies on software post-processing, while the co-registration of TLS Leica multiple linear scans relies on the angular accuracy of hardware. Therefore, the data co-registration mechanism of TLS iPad is slightly different from TLS Leica. The instrument was set up in four locations to capture each corner of the room (Fig. 7a), and the resulting four datasets were co-registered using CloudCompare's ICP registration (Fig. 7b).

This study focuses on the discussion of scan-to-BIM using iPad Pro lidar. The core of scan-to-BIM is to generate a 3D model from a 3D scanner for BIM application. As the 3D model for BIM applications



(a) (b)

Fig. 7. Point clouds obtained by registering the four point clouds: (a) four point clouds obtained at four different locations; (b) registered point clouds.



(a) (b)

Fig. 8. Building the BIM model by point clouds in Autodesk Revit: (a) the floor's building layout; (b) the sectional elevation in Autodesk Revit.

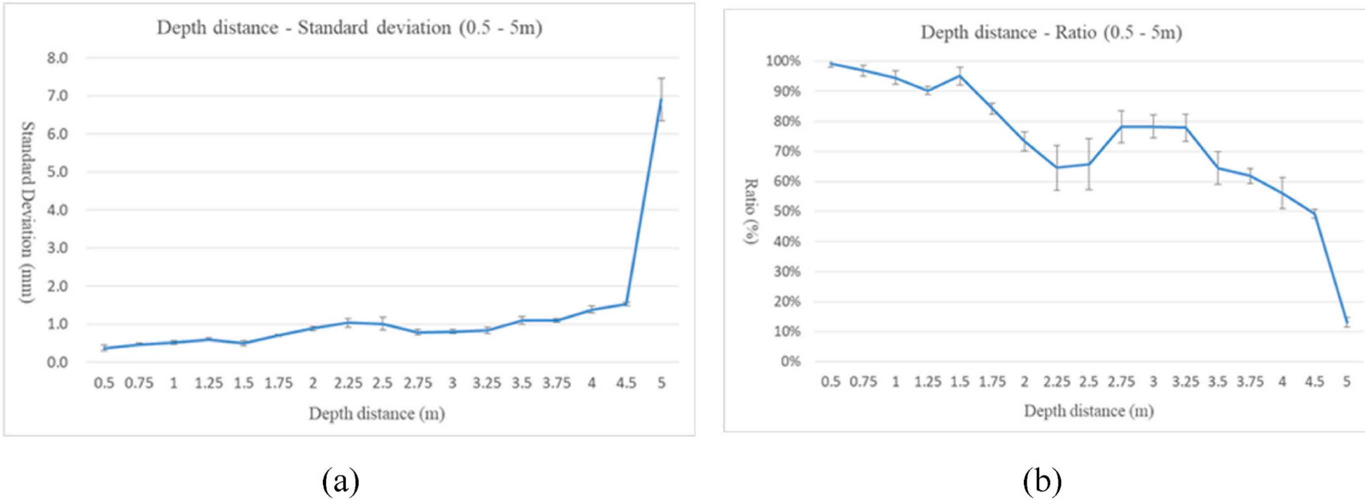


Fig. 9. Relationship between the scanning distance and points' error: (a) the standard deviation of the point-to-plane distances in static acquisition; (b) the ratio of points meeting the 1 mm threshold in static acquisition.

includes geometrical and attribute information for each building element, this study uses one of the popular software (i.e., Autodesk Revit) to create a 3D model together with attributes. The IFC is a basic standard format for exchanging BIM models. The constructed 3D model can be easily exported to IFC using the export function in Revit. Therefore, this study's 3D model (i.e., in.rvt format) can also be converted to the IFC model for exchange (i.e., in.ifc format).

To minimize the errors caused by automatic processing, this study manually built the BIM model from point clouds using Autodesk Revit 2022. The scan-to-BIM process was facilitated by a plug-in software, Undet, which imported the point clouds into Revit and transformed them into each floor's building layout (Fig. 8). The first step of the workflow involved loading the point clouds into the floor's building layout and sectional elevation. The second step was to align the floor in the point clouds with the reference elevation line to define the model's starting and ending heights. The point cloud's intensity was used to locate elements such as the walls, beams, and pillars. The pillars were plotted first, followed by the beams and walls, with frequent switching between the floor's building layout window and the sectional elevation window to account for varying wall heights. Finally, the floor was drawn, and the windows and doors were added to enhance the model's appearance. After building the BIM model from the point clouds, its dimensions were compared to the reference dimensions as absolute accuracy. The BIM's dimensions were measured in Revit, while the reference dimensions were obtained using the Leica Disto D810 ranger.

3. Results and Discussions

The evaluations were conducted in three stages. In the first stage, the accuracy of the iPad Pro in static acquisition was evaluated using a tripod. In the second stage, the point clouds obtained from the iPad Pro and GeoSLAM were compared in handheld dynamic acquisition. This experiment was conducted in an indoor two-floor environment. In the third stage, we analyzed the accuracy of the BIM model reconstructed from the point clouds obtained from motion control and handheld dynamic acquisition. To quantitatively verify the accuracy, in-situ laser ranger measurements were used to calculate the absolute errors.

3.1. Accuracy analysis of static acquisition

In this study, a static acquisition experiment was conducted to evaluate the flatness of the point clouds obtained by scanning a flat surface using an iPad Pro. For each scan, the best-fitting plane was calculated, and the statistical data of the P2P distances (mean and standard deviation) were provided for comparison. The statistical data provided the flatness metrics for comparison at different distances (0.5 m–5 m), and a pre-defined 1 mm P2P distance was used to check the proportion of the points fulfilling the requirement.

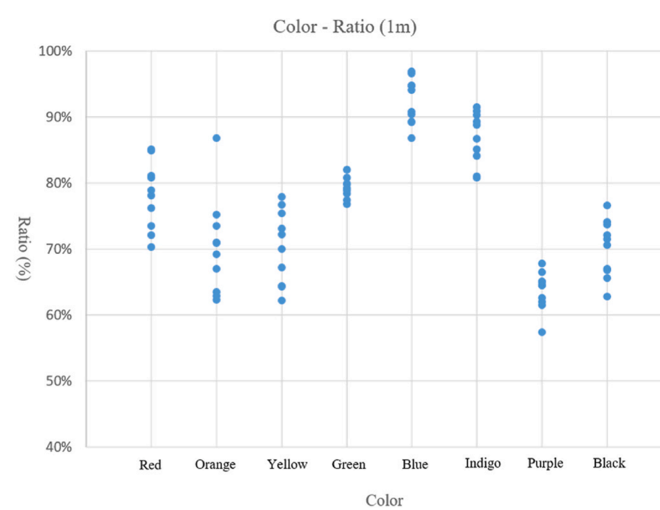


Fig. 10. Dot plot of the ratio results according to the different target colors. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Fig. 9a presents the relationship between the scanning distance and the standard deviation of the P2P distances. The results showed that the standard deviation was proportional to the distance between the iPad Pro and the scanning surface. The standard deviations were better than 2 mm before 4.5 m, but rapidly increased after the depth distance of 4.5 m, which was close to the iPad Pro's maximum scanning distance (5 m). Thus, larger errors were observed for the scanning depths close to the maximum distance compared to those closer to the device.

Furthermore, Fig. 9b shows the percentage of the P2P distances fulfilling the 1 mm requirement with respect to the scanning distance. The results indicated that about 90% of the P2P distances were below 1 mm when the scanning distance was less than 1.5 m. However, the proportion decreased to 60% when the scanning depth distance reached 4 m, and only 13% fulfilled the requirement at a scanning distance of 5 m. Despite possible environmental influences on the scanning data, the study ensured careful data collection in an indoor environment and observed less than 15% variation in each distance. The experimental

Table 1
Ratio of points meeting the threshold in dynamic acquisition.

iPad Pro					
	Threshold (1 mm)	Threshold (1 cm)		Threshold (1 mm)	Threshold (1 cm)
Wall_01	11.79%	90.57%	Floor_01	16.54%	93.19%
Wall_02	9.89%	81.27%	Floor_02	51.22%	100.00%
Wall_03	12.45%	90.36%	Floor_03	32.90%	98.86%
Wall_04	22.64%	94.97%	Floor_04	13.40%	85.33%
Wall_05	3.32%	49.82%	Floor_05	27.37%	90.98%
Wall_06	24.49%	98.30%	Floor_06	10.88%	78.00%
Wall_07	8.79%	66.21%	Floor_07	14.74%	96.60%
Wall_08	16.14%	94.44%	Floor_08	21.81%	96.59%
Wall_09	0.57%	42.72%	Floor_09	6.19%	94.43%
Wall_10	61.90%	100.00%	Floor_10	15.70%	86.68%

results demonstrated that the percentage of points fulfilling the 1 mm requirement was inversely proportional to the scanning distance. In summary, the distance between an iPad Pro and the scanning target should be between 1 m and 1.5 m. Considering the completeness and point density, Bobrowski et al. (2023) observed that distances between 1 and 2 m are more appropriate when using the iPad Pro in forest applications. Therefore, for indoor and outdoor applications, distances less than 2 m are most suitable when using an iPad Pro.

This section presents an analysis of the influence of target color on distance measurement using an iPad Pro's lidar. Seven different colors were tested in this experiment. The percentage of points whose distance was less than 1 mm P2P distance was calculated and compared for each target color. As shown in Fig. 10, the percentage of points meeting this requirement ranged from 60% to 80% regardless of the target's color. The numerical difference between the colors, including red, orange, yellow, green, blue, indigo, purple, and black, was found to be minimal. As no noticeable differences in the flatness were observed between the light and dark colors, it was difficult to categorize the results based on this disparity. Although the blue and indigo targets performed particularly well, no clear trend was observed between the colors. Overall, the results suggest that the color of the target has a random effect on the scanning accuracy of an iPad Pro's lidar. Additionally, it should be noted that the dToF technique used in an iPad Pro's lidar is expected to be less affected by color compared to the indirect time-of-flight technique used in the Kinect v2 (Haider and Hel-Or, 2022), which may be a contributing factor to the sensor's relatively low sensitivity to color. These findings employed an additional metric to supporting Teppati Losè et al.'s (2022) experiment in which Apple's lidar sensor was not considerably influenced by either illumination or the material.

3.2. Accuracy analysis of dynamic acquisition

This section presents the results of the dynamic acquisition task performed using an iPad Pro's lidar sensor, which involved scanning an area comprising two floors and two stairs with a vertical closed-loop path using the RTAB-Map app. The total duration of the scanning process was approximately 5 min, covering a total distance of around 150 m. The resulting co-registered point clouds comprised 453,614 points, with an average density of 300 pt/m^2. As the sensor was mostly facing the floor during scanning, the point cloud data primarily comprised the floor and parts of the wall. Several flat areas were segmented, including the walls and floors, for further analysis of plane fitting and the P2P distance. The accuracy of the scanning was quantified by calculating the ratio of the points that met the accuracy threshold.

Table 1 presents the results of the dynamic acquisition experiment. Due to the inherent variability of dynamic acquisition, less than 20% of the points met the 1 mm threshold in almost every data, thereby making it necessary to use a 1 cm threshold. With the 1 cm threshold, over 80% of the points met the requirement. Due to the dynamic changes of the iPad Pro from time to time during this scanning task, it was reasonable to expect that the performance of the scanning accuracy would not be as high as the result in the previous static acquisition experiment.

The performance of the lidar sensor was observed to vary between the floor and the wall data. Specifically, the floor data exhibited better flatness performance compared to the wall data. This difference in performance can be attributed to the orientation changes of the sensor during scanning. The iPad Pro was primarily facing the floor and moved left and right to obtain the wall data. As a result, the floor was always included in the sensor's field of view and underwent fewer posture changes, whereas the wall on the two sides was not always contained in each frame, resulting in larger posture changes during scanning. Therefore, the posture changes during scanning was the main reason for the observed differences in accuracy between the floor and wall data.

In this section, GeoSLAM was employed to obtain points clouds of higher accuracy for comparison with the iPad Pro's lidar. The point clouds acquired by GeoSLAM and the iPad Pro were co-registered using the ICP algorithm, which globally minimized the distance between the two datasets. Through quantitative analysis, the C2C distance between GeoSLAM and the transformed point clouds using the iPad Pro was computed. Since the point cloud data acquired by GeoSLAM was used as the reference data in this experiment, to reduce the impact of gaps and discrepancies in coverage between these two datasets (e.g., the ceiling), a predefined 1 m cut-off distance was utilized during C2C analysis. As shown in Fig. 11, the difference between the two point clouds was mostly smaller than 0.20 m. As the iPad Pro's acquisition mainly focused on the floor, most of the large errors appeared to be distributed along the

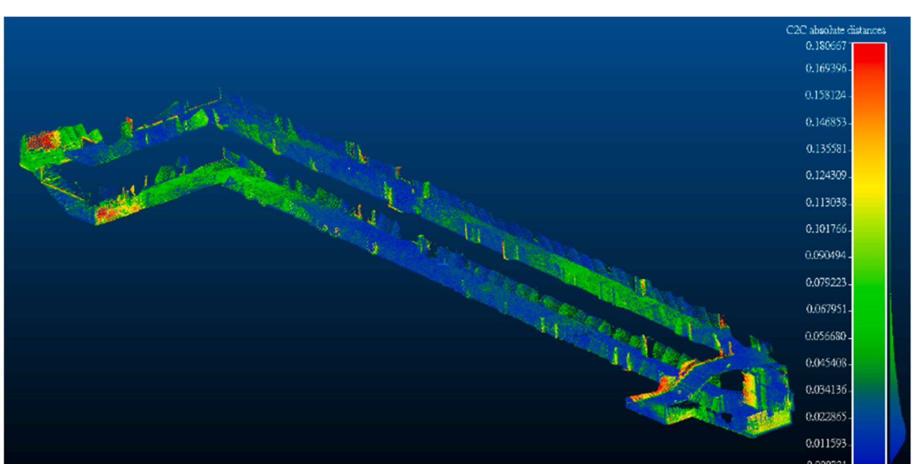


Fig. 11. Results of the cloud-to-cloud analysis between iPad Pro Lidar and GeoSLAM.

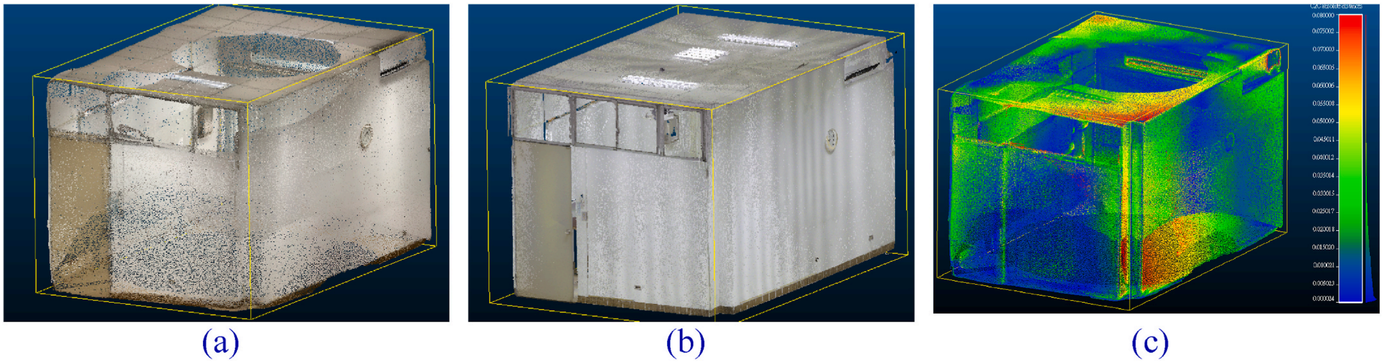


Fig. 12. Comparison of point clouds from the TLS iPad and TLS Leica: (a) point clouds captured by the TLS iPad; (b) point clouds captured by the TLS Leica RTC360; (c) results of the cloud-to-cloud analysis between TLS iPad and TLS Leica RTC360.

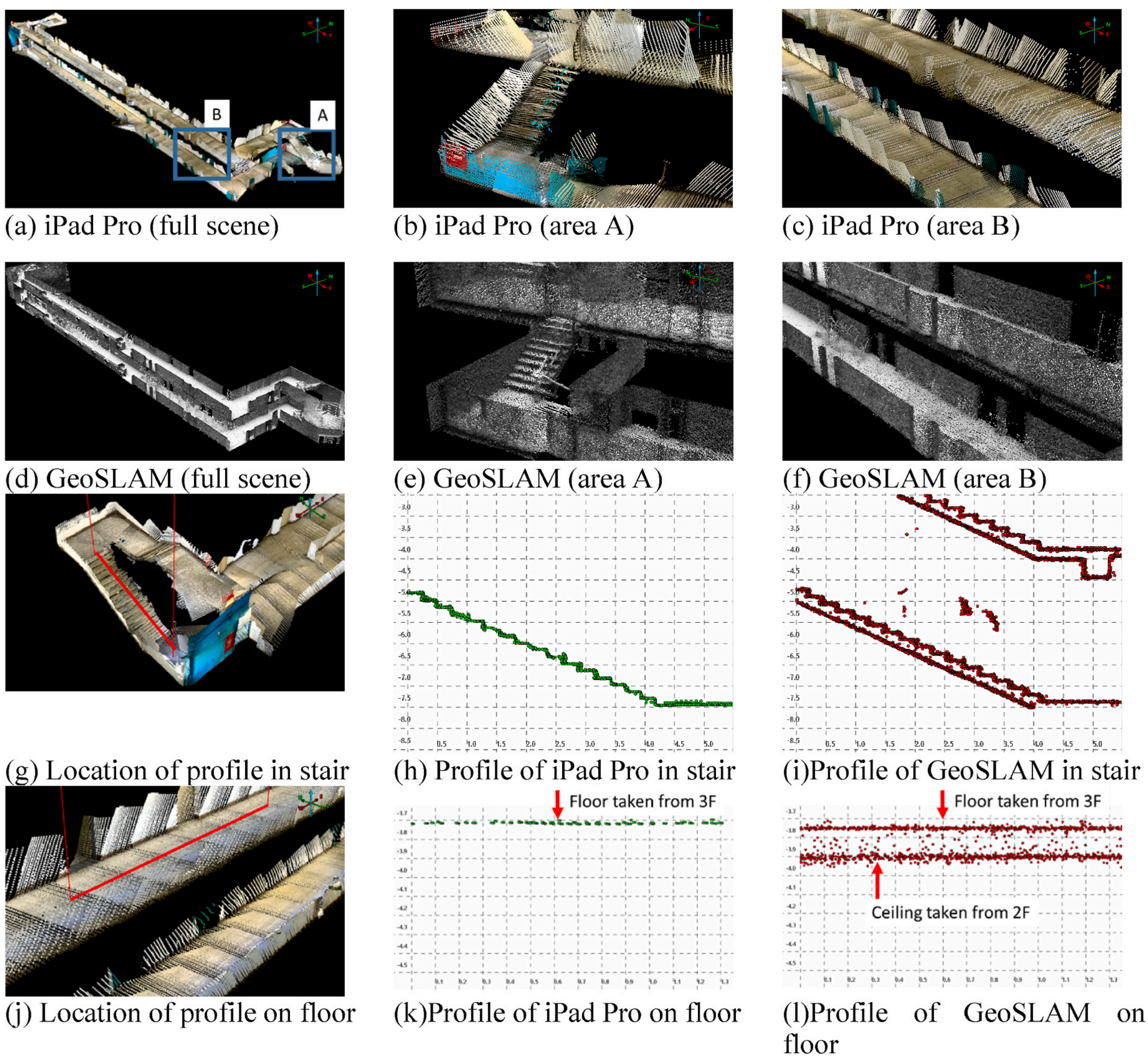


Fig. 13. Comparison of point clouds from the iPad Pro and GeoSLAM: (a)–(c) point clouds captured by the iPad Pro; (d)–(f) point clouds captured by GeoSLM; (g) and (j) location of profiles; (h) and (k) profiles from the iPad Pro; (i) and (j) profiles from GeoSLAM.

walls. The total number of observations was 453,614 points, and the mean C2C distance was approximately 3.9 cm, with a standard deviation of approximately 5.5 cm. Overall, the C2C analysis results indicated differences between the iPad Pro and GeoSLAM. The C2C errors of the floor (marked in blue color in Fig. 11) were smaller than those distributed along the wall (green color in Fig. 11).

To compare the point clouds generated by TLS iPad and TLS Leica RTC360, we acquired data of the same room using the surveying-grade TLS Leica RTC360. While the TLS Leica RTC360 only required 2 stations to acquire the room, the TLS iPad needed 4 stations due to its limitation of frame FOV. Moreover, the average point density of TLS Leica RTC360 (about 54000 pts/m^2) was much higher than that of TLS iPad (about

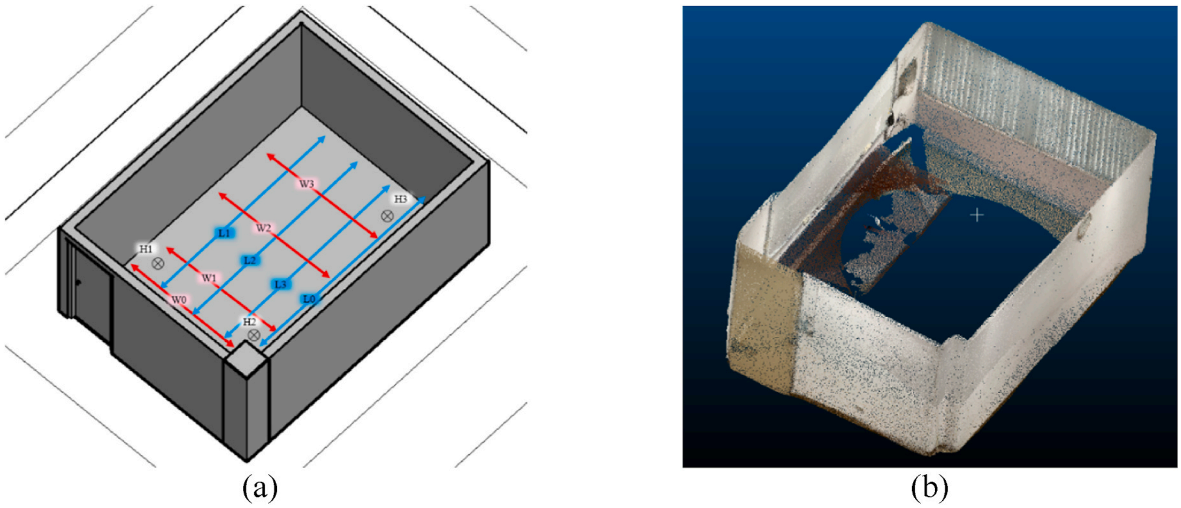


Fig. 14. BIM model and the corresponding point clouds for the scan-to-BIM process: (a) reconstructed BIM model and locations of check lines; (b) point clouds obtained by the iPad Pro's lidar.

Table 2
Comparison between the BIM and the model's true dimensions.

Model 1 (Test area 1)				
	BIM (m)	Reference Dimension (m)	Difference(m)	Error(%)
Length L0	4.450	4.449	0.001	0.02%
Length L1	4.750	4.765	0.015	−0.31%
Length L2	4.750	4.762	0.012	−0.25%
Length L3	4.750	4.760	0.010	−0.21%
Width W0	3.040	3.015	0.025	0.83%
Width W1	3.337	3.321	0.016	0.47%
Width W2	3.337	3.321	0.016	0.47%
Width W3	3.337	3.321	0.016	0.47%
Height H1	2.960	2.960	0.000	0.00%
Height H2	2.960	2.966	0.006	−0.20%
Height H3	2.960	2.966	0.006	−0.20%

7000 pts/m^2), and the average point spacing of TLS Leica (about 0.4 cm) was finer than that of TLS iPad (about 1.2 cm). In this study, we employed automatic ICP fine registration to co-register the TLS iPad and TLS Leica point clouds. The maximum number of sub-sampled points was set at 500,000, with a convergence criterion of the error difference between two iterations being lower than 0.00001. The root-mean-squared error was calculated on a total of 305,444 points and found to be 1.5 cm. We performed a C2C analysis (Fig. 12) with a total of 863,543 points, and the mean C2C distance was approximately 2.4 cm, with a standard deviation of approximately 3.1 cm. Overall, the C2C analysis results indicated that there were differences of about 3 cm between the TLS iPad and TLS Leica RTC360.

In the qualitative check, GeoSLAM was used for undertaking a qualitative comparison with the point clouds generated using the iPad Pro. The point clouds obtained by both devices showed similar overall appearances, as shown in Fig. 13. The iPad Pro demonstrated the ability to capture vertical changes in data. Fig. 13b and c illustrate the stair point clouds obtained by both scanners via handheld dynamic acquisition. Fig. 13h and i compare the profiles from both scanners, where steps in the stairs can be identified in the iPad Pro's data, but the shape from GeoSLAM was more detailed. Fig. 13k and l compare the floor captured by the iPad Pro and GeoSLAM. Notably, GeoSLAM could scan the ceiling of the stair, but the iPad Pro did not contain the point clouds of the ceiling. Fig. 13e and f depict the point clouds on the floor of the corridor, where GeoSLAM obtained more complete wall information than the iPad Pro. The point density of the iPad Pro on the floor was about 500 pt/m^2, while the point density of GeoSLAM was about 1600 pt/m^2. The point density of GeoSLAM was higher than that of the iPad Pro. Additionally, the scanning angle for GeoSLAM was 360° in the vertical and horizontal directions, whereas the field-of-view of the iPad Pro was approximately $60^\circ \times 48^\circ$. Therefore, GeoSLAM could cover a larger area than the iPad Pro.

3.3. Accuracy analysis of the reconstructed 3D BIM models

3.3.1. Evaluation using the iPad Pro's lidar for scan-to-BIM application in a small room

After implementing the scan-to-BIM process, a BIM model of the meeting room was constructed. Fig. 14 shows a comparison between the dimensions of the BIM model and the actual dimensions of the meeting room. To evaluate the accuracy, length, width, and height measurements were taken thrice. Measurements from the wall to the pillar were also taken. Table 2 presents the results of the accuracy analysis, revealing that the dimensional error was less than 1% for all measurements. In summary, using the iPad Pro to obtain point clouds and perform scan-to-BIM in a room was viable. When the scanning areas were limited in size, the mode's accuracy was good, with errors typically kept under 1%. Additionally, mounting the iPad Pro on a motion control device improved the instrument's stability during scanning, resulting in better outcomes.

The regulation document provided by U.S. General Services Administration (USGSA, 2009) was used as a reference to compare the level of detail of scan vs BIM. The regulation has been designed to compare the BIM model and the corresponding point clouds with five levels of detail. The higher the level of detail, the higher the accuracy. For instance, the tolerance for level 1 was less than 51 mm, while the tolerance for level 5 was less than 3 mm. The base category included point cloud, plan, and elevation. Point cloud indicates the distance between two points in a point cloud compared to the reference distance between the same two points in the actual scene. Plan implies the 2D horizontal length of the model and the reference length, while elevation indicates the height of the model and the reference height. To meet the level 2 criteria, the error should be less than 13 mm. According to the accuracy analysis of this BIM model presented in Table 2, the plan and elevation distance errors ranged from 6 mm to 25 mm. Therefore, the point clouds obtained from the iPad Pro's lidar and motion control partially fulfilled the requirements of level 2. In summary, this task could not fully meet the level 2 requirements; however, it came close to meeting the USGSA standards.

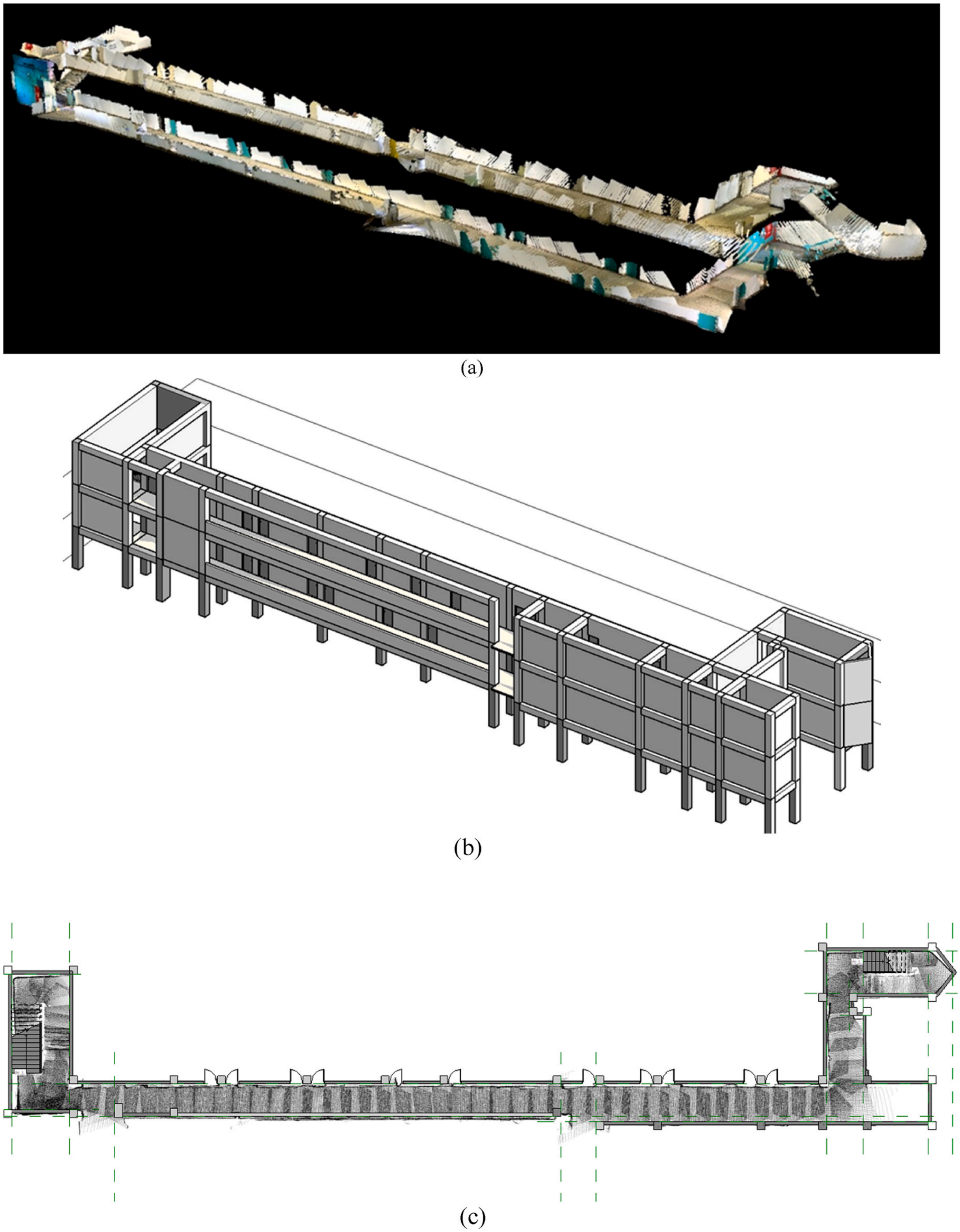


Fig. 15. Comparison between the point clouds and BIM in Revit: (a) point clouds obtained using the iPad Pro's lidar; (b) reconstructed BIM model using the point clouds; (c) overlapped point clouds and the BIM model from the top view.

3.3.2. Evaluation using the iPad Pro's lidar for scan-to-BIM application in a large area

The Scan-to-BIM process was used to generate a BIM model of the large area based on the point cloud data collected during the dynamic acquisition experiment. A comparison between the dimensions of the BIM model and the actual dimensions of the area is shown in Fig. 15. The accuracy of the BIM model was evaluated by measuring the length, width, and height. Fig. 16 shows the locations of the check lines for evaluating the horizontal and vertical distances. There were 21 horizontal and 20 vertical check lines for evaluating the distances. The size of this test area was about 61 x 9.5 x 4.5 m^3, which was much larger than the previous meeting room (i.e., 4.8 x 3.3 x 3.0 m^3). As shown in Table 4, the relative accuracy in the horizontal direction was better than 7%. However, the maximum measurement distance for the iPad Pro was about 5 m, and the accumulated error of the point clouds reached 1.7 m for check lines longer than 60 m. The error was mainly caused by posture

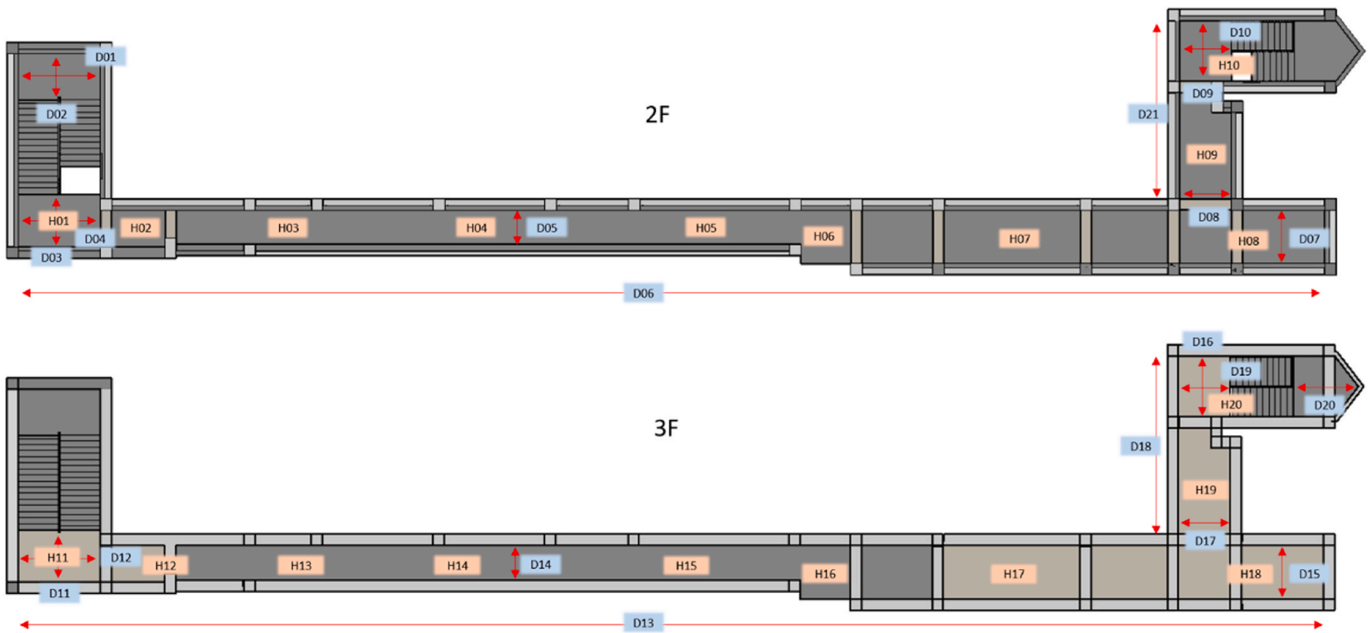


Fig. 16. BIM obtained by undertaking scan-to-BIM of the point clouds in a large area. The analysis was performed by comparing the dimension in the horizontal and vertical directions.

Table 3
Level of detail for levels 1 and 2 of the scan vs BIM regulations provided by the U. S. General Services Administration.

Level of detail	Area of interest	Description	Category	Tolerance (mm)	Minimum artifact size (resolution) mm x mm
Level 1	1	Point cloud	Base	±51	152 x 152
Level 2	2-A	Plan	Base	±13	25 x 25
		Elevation	Base	±13	25 x 25
		Surface model	Option	±13	25 x 25
		Point cloud	Base	±13	25 x 25
	2-B	Elevation	Base	±13	25 x 25
		Surface model	Option	±13	25 x 25
		Point cloud	Base	±13	25 x 25

changes while scanning the area using the handheld iPad Pro. Table 5 shows that there were limited errors in the vertical direction. The BIM built by the scan-to-BIM workflow showed better vertical accuracy than horizontal accuracy. A possible reason could be that the actual height between the floor and ceiling was less than 5 m. The iPad Pro could capture the height between the floor and ceiling directly.

Table 4 illustrates that the error was generally smaller when the verified distance was shorter. The verified distance between two targets within the same scanning frame also leads to a lower error. Based on these findings, we posit that the length of the verified distance may impact the accuracy of the results, and the longer verified distance accumulated more error. Furthermore, it is reasonable to assume that posture changes of the iPad Pro during scanning can also impact accuracy. This was supported by the lower error observed in Fig. 16 when the distance between two targets measured in the same scanning frame indicates no posture changes. To sum up, according to the previous analysis, the static acquisition experiment, the dynamic acquisition analysis, and the evaluation of the scan-to-BIM application, a limited posture change while scanning yields more accurate results. These experimental results suggest that the iPad Pro is only appropriate for mapping small environments. When comparing indoor and outdoor mapping, Díaz-Vilariño et al. (2022) also found that small environments were more suitable for an iPad Pro lidar.

To evaluate the compliance of the scan-to-BIM model with the USGSA's regulations, the accuracy of the model was compared with the regulations outlined in Table 3. The results showed that the model did

Table 4
Comparison between BIM and the true dimensions of the model in the horizontal direction.

	Horizontal Dimensional Difference								
	Model 2 (Test area 2)								
	BIM's length(m)	Actual length(m)	Error (m)	Error (%)		BIM's length(m)	Actual length(m)	Error (m)	Error (%)
Target D01	3.800	3.737	0.063	1.69%	Target D11	2.301	2.415	−0.114	4.72%
Target D02	1.989	1.949	0.040	2.04%	Target D12	3.800	3.963	−0.163	4.11%
Target D03	2.431	2.404	0.027	1.14%	Target D13	60.200	58.462	1.738	2.97%
Target D04	3.800	3.681	0.119	3.23%	Target D14	1.900	1.949	−0.049	2.51%
Target D05	2.100	2.138	−0.038	1.78%	Target D15	2.476	2.330	0.146	6.27%
Target D06	60.200	58.454	1.746	2.99%	Target D16	3.000	3.152	−0.152	4.82%
Target D07	2.476	2.339	0.137	5.87%	Target D17	2.400	2.440	−0.040	1.64%
Target D08	2.400	2.456	−0.056	2.28%	Target D18	8.721	8.797	−0.076	0.87%
Target D09	2.800	2.926	−0.126	4.31%	Target D19	2.490	2.650	−0.160	6.03%
Target D10	2.400	2.472	−0.072	2.91%	Target D20	3.010	3.070	−0.060	1.96%
					Target D21	8.721	8.774	−0.053	0.60%

Table 5
Comparison between BIM and the true dimensions of the model in the vertical direction.

	Vertical Dimensional Difference								
	Model 2 (Test area 2)								
	BIM's height(m)	Actual height (m)	Error (m)	Error (%)		BIM's height(m)	Actual height (m)	Error (m)	Error (%)
Target H01	3.500	3.483	0.017	0.49%	Target H11	3.500	3.469	0.031	0.89%
Target H02	3.500	3.465	0.035	1.01%	Target H12	3.500	3.482	0.018	0.52%
Target H03	3.500	3.485	0.015	0.43%	Target H13	3.500	3.504	−0.004	0.11%
Target H04	3.500	3.478	0.022	0.63%	Target H14	3.500	3.516	−0.016	0.46%
Target H05	3.500	3.489	0.011	0.32%	Target H15	3.500	3.521	−0.021	0.60%
Target H06	3.500	3.491	0.009	0.26%	Target H16	3.500	3.507	−0.007	0.20%
Target H07	3.500	3.480	0.020	0.57%	Target H17	3.500	3.507	−0.007	0.20%
Target H08	3.500	3.473	0.027	0.78%	Target H18	3.500	3.510	−0.010	0.28%
Target H09	3.500	3.476	0.024	0.69%	Target H19	3.500	3.504	−0.004	0.11%
Target H10	3.500	3.474	0.026	0.75%	Target H20	3.500	3.448	0.052	1.51%

not meet the level 2 standard due to the larger size of the scanning area compared to the previous task. Additionally, handheld scanning led to registration errors between the two poses. Therefore, it can be concluded that the point cloud model obtained using the iPad Pro with the motion control device partially achieved level 2 compliance according to the USGSA's regulations when the area's dimensions were smaller than the meeting room in our previous task (4.8 x 3.3 x 3.0 m^3). However, as the dimensions of the area increased, the model's ability to meet the level 2 regulation requirements became more challenging. Overall, the results suggest that minimizing posture changes during scanning can improve the accuracy of scan-to-BIM models in large areas.

4. Conclusions and future works

This study investigated the scanning accuracy of the iPad Pro, which contains a low-cost consumer-grade flash lidar sensor with a maximum scanning distance of 5 m and is suitable for indoor 3D point cloud collection. A systematic analysis was conducted to evaluate the scanning accuracy of the iPad Pro through experiments, and a scan-to-BIM process was applied to the acquired 3D point clouds to discuss the accuracy of the resulting BIM model. 3D Scanner and RTAB-Map Apps were utilized for indoor scanning and modeling. The static acquisition experiment revealed that while scanning a flat surface with a distance of less than 1.5 m, about 90% of the points contained a distance lower than 1 mm to their best-fitting plane. However, when the distance increased to 4 m, the ratio decreased to about 50%, and when the scanning distance was longer than the maximum scanning distance of 5 m, only about 10% of the points achieved the 1 mm threshold. Furthermore, based on the experimental results, the target's color did not have a noticeable impact on the scanning accuracy.

In the dynamic acquisition experiment, an iPad Pro was employed as a handheld moving scanner. The flat surface of the model was segmented and analyzed by the same method used in the static acquisition experiment. Although less than 20% of the points fulfilled the 1 mm threshold, adjusting the threshold to 1 cm resulted in about 80% of the points meeting the 1 cm requirement. The experiment indicated that the relative accuracy of dynamic acquisition was lower than that of static acquisition. The standard deviation of the C2C difference between the point clouds obtained by the iPad Pro and GeoSLAM was 5.5 cm. As the iPad Pro's acquisition mainly focused on the floor, most of the large errors appeared to be distributed along the walls. When implementing a scan-to-BIM application using the point cloud data obtained from the iPad Pro, a small scanning area and a steady scanning pace led to better accuracy. The point clouds obtained using the motion control device after applying scan-to-BIM contained absolute errors smaller than 1%, while the point clouds obtained by handheld scanning contained errors of about 7%. However, scanning a smaller area resulted in better accuracy. The study provides evidence that the iPad Pro's lidar sensor is capable of producing accurate point clouds as well as 3D BIM in certain conditions. However, it still cannot meet the level of accuracy required by the USGSA BIM guide for 3D imaging. Therefore, it is recommended to carefully select laser scanning equipment if a high level of accuracy is required to meet the standards outlined in the USGSA standards.

This study focused on determining an iPad Pro lidar's scanning accuracy and using it in a scan-to-BIM application. Two issues can be addressed in future works. First, since the statistical accuracy of the point clouds was determined in this research, the result provided some indication of using the point clouds. Post-processing of the data, such as off-line pose estimation, may improve the iPad Pro's registration accuracy. Second, the scan-to-BIM process was done manually in this study. Future works can focus on converting the point clouds into BIM automatically.

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Author contributions

Tee-Ann Teo provided the overall conception of this research, designed the methodologies and experiments, and wrote the majority of the manuscript; Chen-Chia Yang contributed to the implementation of proposed algorithms, conducted the experiments and performs the data analyses.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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