Accuracy Assessment of an Image-Based Cloud-Based Indoor Mapping Platform as an Alternative for Desktop Applications

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Abstract:

The generation of 3D spatial datasets, especially in indoor space, has continually been a challenge in developing spatial applications that are aimed for the realistic representation of the real world. Despite their potential, the creation of 3D spatial data remains a challenge, particularly in terms of cost and complexity associated with traditional methods. While this method proves to be a reliable and accurate method of creating such data, this approach entails challenges in economic, computational, and human resource aspects. Alternatively, omnidirectional images have emerged as cost-effective alternatives for representing 3D spaces, offering a comprehensive field of view and facilitating the generation of structure and appearance representations through mesh-based 3D maps. This study evaluates the geometric accuracy of a cloud-based image-based mapping platform for generating 3D representations of indoor spaces, aiming to assess its suitability as an alternative to desktop-based platforms. We obtained 30 sample lines and compare respective measurements from each of the generated meshes to a ground truth value. Results show that while there are no significant differences in the mean errors, the mesh generated from a cloud-based platform produced minimal errors. This demonstrates the potential of this platform for generating 3D representations of indoor space, acceptable in both geometric accuracy and visualization capabilities.

1. Introduction

One promising solution gaining traction is the notion of digital twins (DT), which serve as virtual replicas of physical systems, for solving problems that face urban dwellers in the modern days. These DTs are proving invaluable as a data-driven approach in crafting management strategies driven by real-time data and accurate depictions of the physical environment. Along with big data, cloud computing, and wireless networks, services must be provided to the citizens in a real-time and systematic manner in the goal of improving their quality of life.

Three-dimensional (3D) spatial datasets form the backbone of these DTs, as these data are used in representing the physical world in digital form, enabling the use of allied technologies in developing location-based applications, such as for navigation both in indoor and outdoor space. However, creation of accurate and realistic 3D spatial data has proven to be one of the most pressing challenges in various aspects. Laser scanning, which is the most common method to model indoor spaces (Xiong et al., 2013), entail expensive equipment for data collection, machine and software for data processing, and especially trained professionals across the workflow.

Numerous research papers have shown that as an alternative to laser scanning data, omnidirectional images are viable alternatives for representing 3D spaces, while maintaining an economically and computationally inexpensive methodology (Jung and Lee, 2017; Claridades et al., 2018, 2023). Omnidirectional images deliver a 360-degree field of view at the location of image capture, ensuring a realistic visualization of space (Ahn et al., 2020).

Studies have shown that such omnidirectional images may be used to generate structure and appearance representations through mesh-based 3D maps (Pretto et al., 2011). Conventionally, these meshes generated from triangulation of image tie points are generated from drone images (Domingo et al., 2018; Kikuchi et al., 2022), especially in the macro-scale environment. In the micro scale, its application in generating models for indoor path planning (Han et al., 2022) and façade mapping (Tu et al., 2021), but the metric accuracy of these models for modeling spaces in buildings have been understudied.

Additionally, desktop applications such as Agisoft (Agisoft, 2024) and Pix4D Mapper (Pix4D SA, 2024) have been used for macro-scale 3D photogrammetric mapping, and these require significant computing power and memory for processing sufficient images to produce accurate representations. Conversely, cloud-based applications such as Matterport (Matterport, 2024) provide alternative options for processing images by alleviating computing and memory needs from local machines, while also generating meshes of similar visualization capabilities. This study aims to evaluate the geometric accuracy of a cloud-based image-based mapping platforms for generating 3D representations of indoor space order to examine its potential as an alternative to desktop-based platforms.

The paper is structured as follows. The second section discusses existing studies related to image-based 3D mapping in both macro and micro scale environments. The next section discusses the methodology, followed by a section on an experimental implementation on sample data on a study site. The final section summarizes the findings of this paper and discusses recommendations for future work.

2. Related Work

Amid challenges, cities worldwide are turning to DT technology as a solution to urbanization problems and to support city planning, design, and community engagement (Angelidou, 2017).

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DTs create virtual replicas of physical environments, enabling a simultaneous representation of underlying phenomena, including spatial relationships. Essential to the implementation of DTs is the integration and interoperability of spatial datasets, ensuring accurate representation and analysis of real-world scenarios (Lu et al., 2020; Retscher and Thienelt, 2004). By simulating events and solutions, DTs empower governments and organizations to make data-driven decisions and enact policies that address urban challenges effectively. With DTs increasingly becoming a cornerstone of smart city planning, their application in urban environments promises to revolutionize decision-making processes and improve the quality of life for residents (Giudice, Walton, & Worboys, 2010).

In today's rapidly evolving urban environments that these DTs represent, complexities have arisen due to the fast expansion of population and corresponding human activities. These complexities, such as less familiarity with spatial layouts (Vanclooster and De Maeyer, 2012), have spurred the requirement for mobility-related LBS. However, the fragmentation of datasets and limitations in generating such data hinder the development and provision of effective location-based services (Retscher and Thienelt, 2004). Moreover, as macroscale applications in GIS have developed sooner than indoor microscale applications (Giudice et al., 2010), generating data for indoor space representation is still a challenge.

Numerous studies have used image data to generate 3D representations through mesh representations. In the natural environment, Domingo et al. (2017) generated 3D visualizations of mangrove and aquaculture environments (Domingo et al., 2017), focusing the comparison of the visual aspect of the model across platforms, rather than geometric accuracy. Such accuracy assessment for drone-source photogrammetric meshes has been performed, but focuses on macro environments with vegetative cover, offering flexibility in the image capture device, image capture method and data processing (Barba et al., 2019). Similar methodologies have been used to evaluate facades of rock formations (Tu et al., 2021).

In built environments, while laser scanning has shown effective results in generating semantically-rich 3D building models, (Xiong et al., 2013), drone data has been used for landscape visualization for DT development (Kikuchi et al., 2022) to generate extensive city models for developing an augmented reality-based LBS. Imagery has also been used in 3D modeling of buildings for a campus-based digital twin development (Lu et al., 2020). However, accuracy assessment of such models has been unexplored so far.

In the indoor environment, literature focuses on identifying methods for solutions tailored specifically to navigate the complexities of indoor environments. Han et al. (2022) proposes grid-optimized algorithms to confront this challenge head-on, offering a novel approach to reduce computational complexity and optimize flight paths within intricate indoor spaces. Their methodology partitions indoor airspace into manageable grids, effectively streamlining modeling processes while enhancing the efficiency of path planning algorithms (Han et al., 2022). By introducing a systematic means of representing indoor environments, this presents a promising avenue toward overcoming the computational hurdles that traditionally hinder UAV navigation in indoor settings.

Similarly, Aleksandrov et al. (2021) introduced an automatic abstraction method for pedestrian dynamics using navigation mesh. Leveraging sophisticated spatial indexing techniques, their methodology facilitates rapid extraction of crucial features required for realistic pedestrian simulations (Aleksandrov et al., 2021).

Additionally, Hong et al. (2013) proposes a semi-automatic method for constructing comprehensive 2D and 3D indoor maps, offering insights into the challenges inherent in preprocessing, mapping, and modeling indoor environments. By providing a systematic approach to indoor mapping, their methodology lays the groundwork for creating detailed representations of indoor spaces, essential for various applications such as navigation and facility management (Hong et al., 2013). Similarly, Hübner et al. (2021) present a voxel-based indoor reconstruction approach, offering automation and versatility in handling unstructured triangle meshes to derive semantically-enriched indoor models. Their methodology, which does not rely on planar room surfaces or clear vertical subdivisions, showcases the potential of advanced computational methods in generating comprehensive indoor representations, vital for building information modeling and other related fields (Hübner et al., 2021).

These studies collectively underscore the importance of leveraging advanced computational techniques to unravel the intricacies of indoor navigation, thereby opening avenues for enhanced usability and safety within indoor spaces. However, the geometric accuracy of models generated from images for representing indoor space is still underexplored in published studies.

Pix4D and Agisoft are both desktop-based software solutions used in photogrammetry and drone mapping. These programs enable users to create 3D models and maps from aerial imagery captured by drones or other sources (Agisoft, 2024; Pix4D SA, 2024). Pix4D and Agisoft process images taken from various angles and positions, utilizing algorithms to reconstruct the geometry and texture of the surveyed area. These platforms are commonly used in industries such as agriculture, construction, mining, and surveying for tasks like terrain mapping, volumetric analysis, and asset inspection. 3D modeling workflows are available in these platforms, particularly the use of omnidirectional images for the 3D modeling of indoor spaces (Pix4D SA, 2017).

On the other hand, Matterport offers a different approach to spatial data capture and visualization. Matterport provides hardware and software solutions for creating immersive 3D models of interior spaces, primarily used in real estate, architecture, and interior design (Matterport, 2024). Matterport's technology involves capturing omnidirectional images and then stitching them together to create a virtual tour or model of the space. Unlike Pix4D and Agisoft, which focus on outdoor mapping and photogrammetry, Matterport specializes in indoor environments, providing a user-friendly platform for creating interactive virtual tours and spatial documentation. It is a cloud-based application, referring to the storage and processing of the 3D data on remote servers accessible via the internet, enabling users to access and interact with their digital twins from anywhere with an internet connection.

While desktop applications are hindered by physical limitations of machine and memory, a cloud-based approach offers scalability, ease of access, and collaboration capabilities, making it convenient for users to manage and share their 3D content. This paper aims to address the above-mentioned gap in literature by conducting an accuracy assessment of 3D meshes generated from omnidirectional image data.

3. Methodology

Figure 1 describes the overall methodology of this study. The data collection component is composed of the image capture process and the collection of in-situ measurements of actual object in the study area. The data processing part is composed of the image stitching process and the generation of the meshes from the desktop and cloud-based platforms. Finally, the accuracy assessment consists of comparing measurements done in the generated meshes from the in-situ measurements.

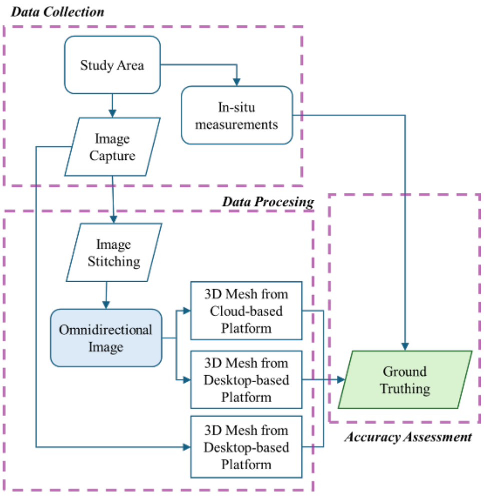

Figure 1. Overall methodology of the study

Points where images are captured, referred to as shooting points, are identified in the study area for image capture. Depending on the camera lens type and parameters, multiple images may be taken within a single shooting point to capture an omnidirectional image at that location. This means that using a camera with wider lens field of view reduces the number of raw images to be captured to generate an omnidirectional image and removes the image stitching step. In particular, in the case of multiple images taken within a single point, an image stitching step is performed to generate an omnidirectional image to represent that shooting point. Figure 2 shows the process of stitching multiple shooting points to generate an omnidirectional image. If an omnidirectional camera is used, there is no need for this step.

Figure 2. Stitching raw images to form omnidirectional images

Three methods are used to generate the mesh data. The first two methods involve using the omnidirectional images in a desktop-based platform and a cloud-based platform to generate a 3D mesh. The third method is using the Pix4D best practices method in collecting images in indoor space for the purpose of generating a 3D mesh model. This method involves moving the back of the image to the wall and shooting at 90 degrees (Pix4D SA, 2017).

Figure 3 shows the image capture strategy suggested by Pix4D to generate the most well-distributed matches on the images. In the figure, the orange line represents the wall, while the purple arrow represents the path of the image capture operation. The green lines show the direction of the shooting, with the camera placed near a wall and shooting towards the direction of the opposite wall. Full processing options are selected in order to obtain the maximum resolution of the 3D model possible from the omnidirectional images.

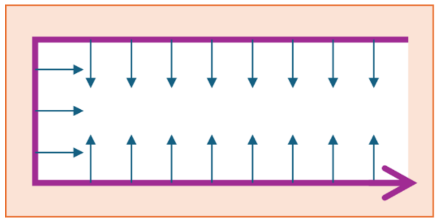

Figure 3. Image capture method suggested by Pix4D

After the 3D three meshes are generated, sample measurements are taken within the study area, as well as their corresponding digital representations in each of the three meshes. In order to evaluate the geometric accuracy of the models, measurements on the study are used as ground data for comparing the measurements of the same objects on the mesh datasets. To quantify the differences in measurement, Equation 1 and Equation 2 are used to calculate the Root Mean Square Error (RMSE) and the Error Standard Deviation, respectively.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{x}_i - x_i)^2}{n}}, \quad (1)$$

where $\hat{x}_1, \hat{x}_2, \dots, \hat{x}_i$ = true distance value
$x_1, x_2, \dots, x_i$ = observed distance value
n = number of observations

$$\sigma = \sqrt{\frac{\sum(\Delta_i - RMSE)^2}{n}}, \quad (2)$$

where $\Delta_i, \Delta_i, \dots, \Delta_i$ = error values
n = number of observations

Moreover, to analyze the statistical significance of the errors, we have to perform a one-way analysis of variance (ANOVA) test to determine if there are significant difference between the mean errors. The f-statistic for the ANOVA test to test for significance for the mean is calculated using Equation 3.

$$F = \frac{MSB}{MSW}, \quad (3)$$

where MSB = Mean Square Between Groups
MSW = Mean Square Within Groups

Each of these components, in turn, are calculated using Equation 4 and Equation 5.

$$MSB = \frac{SSB}{dfB}, \quad (4) \qquad MSW = \frac{SSW}{dfW}, \quad (5)$$

where MSB = Sum of Squares Between Groups
MSW = Sum of Squares Within Groups

On the other hand, an F-test is used to test for significance for the mean is calculated using Equation 6.

$$F = \frac{s_{max}^2}{s_{min}^2}, \quad (6)$$

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where s_{max}^2 = Maximum sample standard deviation, squared
s_{min}^2 = Minimum sample standard deviation, squared

Additionally, the degrees of freedom used for checking the critical F-value is calculated using Equation 7 and 8.

$$df_1 = k - 1, \quad (7) \qquad df_2 = n - 1, \quad (8)$$

where k = number of groups
n = total number of observations

4. Experimental Implementation

An experimental implementation is conducted on a sample data collected on a sample site on a university campus. PTGui 10.12 was used to stitch the raw images to generate omnidirectional images. The image capture device used is a GoPro Hero 4, and we used Pix4D 4.6.4 as a and Matterport as the desktop-based and the cloud-based mesh generation platforms. Table 1 summarizes the experimental environment and Figure 4 shows the study area and the respective shooting points.

Study Area	Kamagong Residence Hall, UP Diliman Campus
Image Capture Device	GoPro Hero4 Black
Image Stitching	PTGui 10.12
Desktop-based Modeling	Pix4D 4.6.4
Cloud-based Modeling	Matterport

Table 1. Experimental Environment

Figure 4. Study area and locations of shooting points

At each of the shooting points, we collected 12 images to ensure sufficient overlap. Each set of points are stitched in PTGui to generate the six omnidirectional images in Figure 5.

Figure 5. Omnidirectional images for the study site.

The first mesh is generated using the Pix4D-suggested image capture method and is processed using Pix4D. The camera positions and rays are shown in Figure 6, showing the direction of image capture as coming from opposite the walls. The resulting generated mesh is shown in Figure 7.

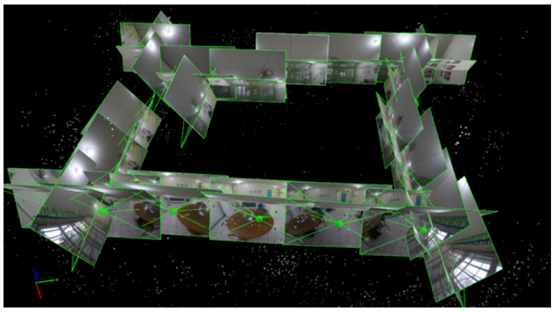

Figure 6. Camera positions for the first capture method

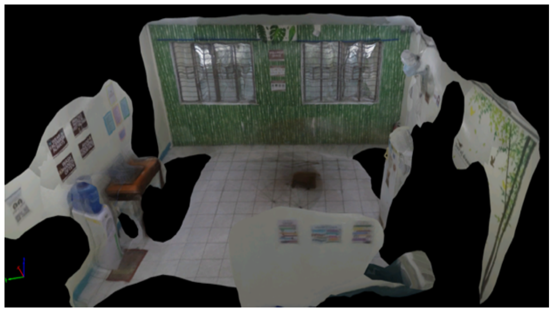

Figure 7. Mesh generated from the image capture method suggested by Pix4D best practices

The second mesh is generated using the six omnidirectional images collected from the shooting points and is processed in Pix4D. Figure 8 shows the camera positions and the rays produced correspondingly. Figure 9 shows the generated mesh from this method, shown at different perspectives. It can be observed that the resulting mesh is similar to the result from the method suggested by Pix4D for ensuring a maximum number of image matches.

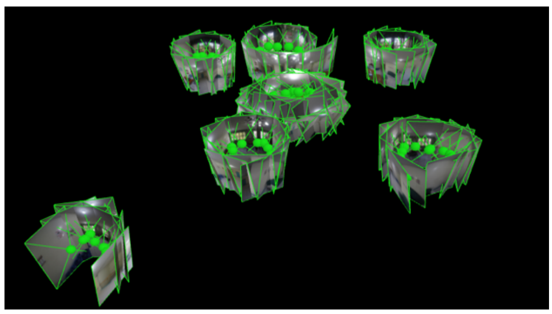

Figure 8. Camera positions from omnidirectional image capture

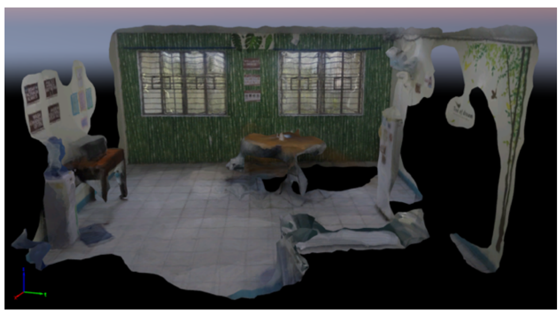

Figure 9. Mesh generated from the desktop-based platform using omnidirectional images

Finally, the same set of omnidirectional images are used as 3D scans in Matterport. In Matterport, each omnidirectional image is used as a 3D scan, and a similar process of image matching is performed in the cloud. Figure 8 shows the positions of the shooting points, oriented as 3D scans in Matterport. Figure 9 shows a capture of the generated 3D mesh.

Figure 10. 3D scans oriented and aligned in Matterport

Figure 11. Mesh generated from the cloud-based platform using omnidirectional images

In order to compare the results of the various mesh generating methods, we measure 30 lines on the study area using a measuring tape (least count: 1 cm) and measured the length of the same 2D segments in the three meshes. A subset of the sample lines, their in-situ measurements, and illustrations are shown in Table 2. Table 3 shows the result of the accuracy analysis on the sample data.

Line 1: 54.94 cm		Line 3: 53.34 cm		Line 7: 44.45 cm	
Line 2: 114.3 cm		Line 4: 30.48 cm		Line 12: 40.64 cm	

Table 2. Sample subset of the data collected for accuracy assessment

	True Value	Mesh 1	Error	Mesh 2	Error	Mesh 3	Error
Line 1:	154.94	141.99	-12.95	126.52	-28.42	149.86	-5.08
Line 2:	114.30	106.73	-7.57	94.77	-19.53	116.84	2.54
Line 3:	53.34	49.73	-3.61	42.86	-10.48	50.80	-2.54
Line 4:	30.48	28.30	-2.18	25.32	-5.16	30.48	0.00
Line 5:	29.21	27.56	-1.65	24.71	-4.50	30.48	1.27
Line 6:	76.20	72.19	-4.01	63.61	-12.59	73.66	-2.54
Line 7:	44.45	39.57	-4.88	32.79	-11.66	43.18	-1.27
Line 8:	33.02	32.82	-0.20	28.02	-5.00	35.56	2.54
Line 9:	20.32	18.72	-1.60	17.04	-3.28	20.32	0.00
Line 10:	53.34	51.74	-1.60	45.75	-7.59	50.80	-2.54
Line 11:	25.40	29.36	3.96	21.03	-4.37	22.86	-2.54
Line 12:	40.64	40.11	-0.53	30.49	-10.15	45.72	5.08
Line 13:	81.28	76.58	-4.70	67.51	-13.77	76.20	-5.08
Line 14:	27.94	27.36	-0.58	24.03	-3.91	27.94	0.00
Line15:	27.94	27.43	-0.51	22.02	-5.92	30.48	2.54
Line 16	27.94	22.73	-5.21	19.86	-8.08	35.56	7.62
Line 17:	91.44	89.74	-1.70	76.16	-15.28	83.82	-7.62
Line 18:	87.63	82.09	-5.54	72.97	-14.66	81.28	-6.35
Line 19:	48.26	46.10	-2.16	40.98	-7.28	48.26	0.00
Line 20:	35.56	31.50	-4.06	26.52	-9.04	30.48	-5.08
Line 21:	35.56	30.63	-4.93	26.66	-8.90	33.02	-2.54
Line 22:	22.86	21.01	-1.85	19.22	-3.64	22.86	0.00
Line 23:	78.74	72.49	-6.25	62.99	-15.75	78.74	0.00
Line 24:	60.96	57.07	-3.89	51.27	-9.69	60.96	0.00
Line 25:	81.28	62.74	-18.54	50.45	-30.83	83.82	2.54

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Line 26	91.44	85.17	-6.27	77.61	-13.83	91.44	0.00
Line 27:	33.02	27.71	-5.31	24.96	-8.06	33.02	0.00
Line 28:	121.92	114.45	-7.47	103.70	-18.22	127.00	5.08
Line 29:	152.40	144.22	-8.18	129.29	-23.11	154.94	2.54
Line 30:	91.44	86.77	-4.67	77.61	-13.83	99.06	7.62
		RMSE	10.24	**RMSE**	23.33	**RMSE**	6.41
		STD. DEV.	4.21	**STD. DEV.**	7.16	**STD. DEV.**	3.53

Table 3. Results of the accuracy assessment

On the Mesh 1 column are measurements for the mesh generated using the Pix4D-recommended capture method. The Mesh 2 column contains the measurements on the mesh generated from omnidirectional images processed in Pix4D. The Mesh 3 column are measurements on the mesh in Matterport. The columns beside each of those are errors obtained by subtracting the actual measurements from mesh measurements. At the bottom of the table are RMSE and Standard Deviation values. Results in Table 3 show that the mesh from Matterport (Mesh 3) give the lowest RMSE, while the mesh generated from the omnidirectional images (Mesh 2) produce the largest errors. The errors are more consistent too, in Mesh 3, evidenced by the smallest standard deviation.

In order to analyze the results further, a statistical test for significance is performed. The analysis conducted includes both an ANOVA test for comparing means and an F-test for comparing standard deviations (SD) of the errors for three meshes. For the means, the ANOVA test indicates no significant difference among the mean errors of Mesh 1, Mesh 2, and Mesh 3. However, for standard deviations, the F-test suggests significant differences in variability across all three meshes. This implies that while the mean errors do not vary significantly between the meshes, the variability in error values differs significantly. Therefore, while the average errors may be similar across the meshes, the consistency or spread of errors varies significantly among them.

Based on these results, it can be inferred that the development of Location-based services, especially in complex urban environments can significantly benefit from cloud-based platforms. In such environments, high-precision spatial data is necessary, and said platforms can offer notable advantages over the traditional desktop-based platforms. By leveraging the scalability and computational power of cloud infrastructure, cloud-based platforms enable the efficient remote processing of vast amounts of data, effectively addressing the physical and computational limitations often encountered with desktop systems. This may prove to be helpful for managing complex and extensive 3D data that are required in these applications.

The effectiveness and accuracy of spatial applications in urban areas are crucial, and cloud-based platforms are well-suited to meet these demands. These platforms can handle and process data at a much larger scale than desktop systems, ensuring the high-precision spatial data needed for accurate and reliable LBS applications. In processing 3D spatial data from various sources, the enhanced computational power of the cloud can improve the quality of the generated meshes. Studies comparing different mesh generation methods have shown that cloud-based platforms can produce data with lower RMSE and standard deviation, resulting in more consistent and precise outcomes.

Statistical analysis further proves its reliability based on the experimental data. For instance, an analysis comparing meshes generated using different methods—such as those from Pix4D and Matterport—revealed significant differences in error variability. Although the mean errors of the meshes may not differ significantly, ANOVA and F-test indicate considerable variation in the consistency of these errors. Cloud-based platforms enable organizations to make data-driven decisions based on reliable and consistent information. Therefore, the adoption of cloud-based platforms is expected to enhance the efficiency and accuracy of LBS in dense urban environments.

5. Discussion

As mobile phones have become integral to our daily lives, various mobile applications have assisted us in completing tasks that might otherwise seem mundane. Nowadays, it's difficult to imagine leaving our homes without our smartphones, tablets, or laptops, or being in a place without a stable internet connection. Solutions provided by current technology aim to aid in essential tasks people carry out daily, such as navigation. While getting from Point A to Point B may seem straightforward, the fast-paced and intricate nature of urban life demands more precise, dependable, and timely guidance to save time and resources. Location-based service (LBS) applications offer real-time instructions in a portable manner, encouraging multi-modal transportation and potentially leading to significant benefits such as reduced traffic congestion and emissions. In this manner, spatial data becomes an indispensable component as new technologies rise daily.

Developing methodologies for LBS, especially in densely populated cities, requires high-precision spatial data, especially in three dimensions (3D) to account for the complexity of multi-modal transportation and urban environments with varying elevations. While 3D city models accurately represent these intricacies, hardware for storing detailed block models poses challenges due to the large volume of data, which mobile devices may not be capable of handling efficiently. Such devices too, are incapable of handling desktop-based platforms due to physical and computational limitations. Cloud-based platforms offer an alternative to process the data through remote resources.

Moreover, on the data side, to address these challenges, mobile devices and applications must be able to utilize datasets with simple structures given their small disk sizes. However, this this still presents challenges on the backend in cases of high-volume input datasets, such as laser scans. Nowadays, platforms that provide street-level image data to aid navigation are widely in use and these even provide path calculations. Omnidirectional imaging technology offers a promising solution to these challenges. Capture devices for these images, now lightweight and affordable, provide high-resolution representation suitable even for urban areas, which require more shooting locations, and hence, larger data. These images capture detailed map information, offering finer spatial resolution than satellite imagery and enabling real-time updates of rapidly changing urban environments. Furthermore, the simple data structure of omnidirectional images makes them well-suited for applying image-based navigation algorithms (Claridades et al., 2023). This simplicity, and the straightforward data collection approach streamlines both backend development and frontend user experience, potentially enabling seamless indoor-outdoor navigation applications and integrating the indoor and outdoor environment.

Results of the experiment suggest that when comparing the use of cloud-based platforms versus desktop platforms for processing 3D spatial data, there are notable implications. Cloud-based platforms offer a viable alternative to desktop-based platforms, particularly in handling the computational and storage demands associated with large volumes of spatial data. While both types of platforms may yield similar mean errors in 3D model generation, the variability in error values differs significantly. This suggests that cloud-based platforms may offer more consistent results in terms of error distribution across different datasets.

With these, organizations seeking to develop methodologies for Location-Based Services (LBS) in densely populated cities, where high-precision spatial data is crucial, may find cloud-based platforms advantageous. These platforms can efficiently process data remotely, leveraging the scalability and computational power of cloud infrastructure while addressing the limitations of desktop-based platforms in terms of physical and computational constraints. Thus, the adoption of cloud-based platforms for processing 3D spatial data holds promise for improving the efficiency and accuracy of spatial applications in urban environments.

6. Conclusions and Recommendations

Digital twins facilitate data-driven management strategies aimed at improving the quality of life for urban dwellers. Central to the development of DTs are three-dimensional (3D) spatial datasets, which serve as the backbone for representing the physical world in digital form and enabling the development of location-based applications for navigation in both indoor and outdoor spaces.

However, the creation of accurate and realistic 3D spatial data poses significant challenges, particularly in terms of cost and complexity. Traditional methods such as laser scanning require expensive equipment, specialized software, and trained professionals, making them inaccessible for many applications. As an alternative, omnidirectional images have emerged as a viable option for representing 3D spaces, offering an economically and computationally inexpensive methodology. These images provide a 360-degree field of view and can be used to generate structure and appearance representations through mesh-based 3D maps.

The experimental implementation conducted in this study compared the accuracy of 3D meshes generated from omnidirectional images using both desktop-based (Pix4D) and cloud-based (Matterport) platforms. Linear measurements on the models show that larger errors are produced on the model generated from omnidirectional images and in Pix4D, while most accurate measurements come from the same images processed in Matterport. Statistical analysis demonstrated that while both platforms produced similar mean errors in 3D model generation, there were significant differences in the variability of error values. Cloud-based platforms demonstrated more consistent results in terms of error distribution across different datasets, highlighting their potential advantages over desktop-based platforms, particularly in handling the computational and storage demands associated with large volumes of spatial data.

In conclusion, the findings of this study suggest that cloud-based platforms offer a promising alternative to traditional desktop-based platforms for processing 3D spatial data in urban environments. By leveraging remote resources and the scalability of cloud infrastructure, these platforms can efficiently process data while addressing the limitations of desktop-based platforms. The adoption of cloud-based platforms holds potential for improving the efficiency and accuracy of spatial applications, ultimately contributing to the development of smarter and more sustainable urban environments.

This study has several limitations that future studies may aim to address. First, the study area is a small room which limits the number of images used in generating the meshes. The room space is chosen as a study area primarily since omnidirectional images have been used in studies on indoor space modeling (Ahn et al., 2020; Claridades et al., 2023). As such, the simplicity of the area presents a limitation where this experimental implementation does not capture the complexity of the physical world realistically. While the implementation still demonstrates the potential of cloud-based applications in generating 3D models, future studies may explore using such images in larger, more intricate spaces.

This paper’s methodology is designed to compare the errors on the linear measurements on 3D models generated on the same space. Despite the limitation on the space that limits the number of images, this number is kept constant across the generation of the compared models. It can also be observed that in the resulting models, that there are numerous distorted objects and occluded parts of the study area. As this study focuses on the accuracy of the geometric accuracy of the model, other aspects of accuracy metrics such as model completeness, visual accuracy, is not within the scope of this paper. As these limitations in the generated model may be attributed to the limitations in the number of images that are captured inside the space, additional image capture can reduce such model errors. This paper recommends that future studies may explore the trade-off between the increasing data collection and processing burden of additional images within the same space and possible improvement in accuracy, as well as the use of other photogrammetric desktop platforms for generating the 3D model.

Due to economical limitations, the images used to capture omnidirectional images do not have a 360-degree FOV, so a stitching process is necessary, which may introduce errors in distortion and possible errors in generating the mesh. Applying the general methodology for an expanded study area and using a 360-degree camera may expand the insights of the results that may be obtained. Moreover, since the online platform provides a more convenient method for processing, resulting raw meshes may be used for generating BIM data, expanding from a single room towards an entire building.

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