

AI-Augmented Integration of Smartphone LiDAR and Terrestrial Laser Scanning for Enhanced 3D Building Modelling

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Abstract

Artificial Intelligence (AI) is rapidly transforming spatial data acquisition and modelling workflows. The aim of this research focuses on AI-augmented integration of Terrestrial Laser Scanning (TLS) with smartphone-based LiDAR to improve the quality and completeness of 3D building models. Although TLS provides detailed and accurate point clouds, its effectiveness is limited by issues such as occlusions, high costs, and accessibility constraints. Smartphone LiDAR offers a convenient and flexible way to capture data in areas that are difficult for TLS to reach, although it is less precise. In this study, AI techniques were applied to fuse the datasets from both TLS and smartphone LiDAR, filtering out noise and ensuring geometric consistency. The experiment was conducted at Bangunan Wawasan, UiTM Shah Alam, with dimensional accuracy assessed through comparison to Total Station measurements. The results show that TLS alone achieved a Root Mean Square Error (RMSE) of 0.020 meters, while the AI-integrated fusion of TLS and smartphone LiDAR data resulted in an RMSE of 0.025 meters. This small difference confirms that the fusion approach maintains accuracy while expanding spatial coverage. Overall, this work demonstrates that AI-driven integration of diverse LiDAR data sources can effectively address the limitations of individual systems, leading to more complete and accessible 3D models without sacrificing precision.

Keywords: Artificial Intelligence, Data Fusion, Smartphone LiDAR, Terrestrial Laser Scanning

1. Introduction

The integration of AI in geospatial technologies has unlocked new dimensions in 3D modelling, urban planning, and digital reconstruction. The latest advancements in terrestrial laser scanners have led to many different types of applications, resulting in a wider use of laser scanners [1][2][3][4][5][6][7] and [8]. Terrestrial laser scanning (TLS) is very important in many sectors and applications today. Technology breakthroughs have made TLS systems more widely available, dependable, and able to record growing levels of surface detail. This is especially important in sectors like urban planning, where accurate 3D representations of cities are necessary for infrastructure development and emergency preparation. TLS is also being used more and more in environmental monitoring to monitor landscape changes, identify potential risks, and evaluate how human activity affects ecosystems [9]. Furthermore, by offering precise data for design and

analysis, TLS facilitates resource management and improves building projects at times where sustainability and efficiency are of highest priority [10][11][12][13][14] and [15]. In simple terms, in today's evolving world, TLS continues to be at the advance of modern spatial data collecting, promoting innovation and accurate choices across a variety of sectors.

On the other hand, smartphone LiDAR which equipped with AI-powered depth sensing and point cloud generation algorithms has emerged as a compact alternative capable of capturing spatial data in inaccessible zones [16] and [17] or confined spaces which is often to be struggling for TLS to access [18] and [19]. Apple's LiDAR-equipped iPhones and Android's Time of Flight (ToF) sensors leverage machine learning for scene reconstruction, object segmentation, and augmented reality, making them viable tools for structural modelling. The use of

LiDAR added to phones and tablets for geo-spatial data has become an important tool to support the work of experts in various disciplines and reach a broader audience [20][21][22] and [23]. Therefore, a new level of depth and accuracy in building modelling can be achieved by combining data from TLS and smartphone LiDAR. The integration improves the precision and coverage of the models by including more texture, visual details, and information about context [24][25][26][27] and [28]. This is because the portability of smartphone with LiDAR sensor enables data collection in narrow spaces and from high oblique perspectives, addressing 3D data gaps left by traditional methods like Unmanned Aerial System and ensuring a high ground sample distance for detailed data on facade-type environments [29] and [30].

The primary aim of this study is to investigate the AI-enabled integration of TLS and smartphone LiDAR for 3D modeling of built environments. The objectives are to develop a unified 3D model using data fusion techniques supported by AI and to analyse the geometric accuracy of the AI-merged model against conventional TLS-derived models.

2. Methodology

GNSS-IR In this study, the research methodology was divided into four phases where phase one is a preliminary study that focuses on the specified study

area, instruments and software used to process the point cloud data. Phase two involved the usage of three instruments for data collection, and they are Total Station, Smartphone, and TLS. The Total Station has been used as ground measurement. Smartphone LiDAR and TLS have been used to scan the building. Phase three is data processing of two different point clouds. FARO SCENE software has been used to process the data obtained from TLS. The CloudCompare software has been used to fuse the point clouds obtained from Smartphone LiDAR with the point clouds obtained from TLS through AI-driven cloud integration. Then, Autodesk Revit Software has been used to produce a detailed 3D model of the study area. Phase four is the results and analysis of the final of 3D model based on the objectives in this research. Figure 1 shows the detailed methodology of this study.

2.1 Preliminary Study

The study area is located at the stairs at Bangunan Wawasan in UiTM Shah Alam, Selangor as shown in Figure 2. This site has been chosen because there will be part of the structure that cannot be scanned by using TLS especially the area under the stair. Three instruments been used in this study and they are TLS, Total Station and Smartphone LiDAR. Total Station has been used for collecting benchmarking data for accuracy assessment.

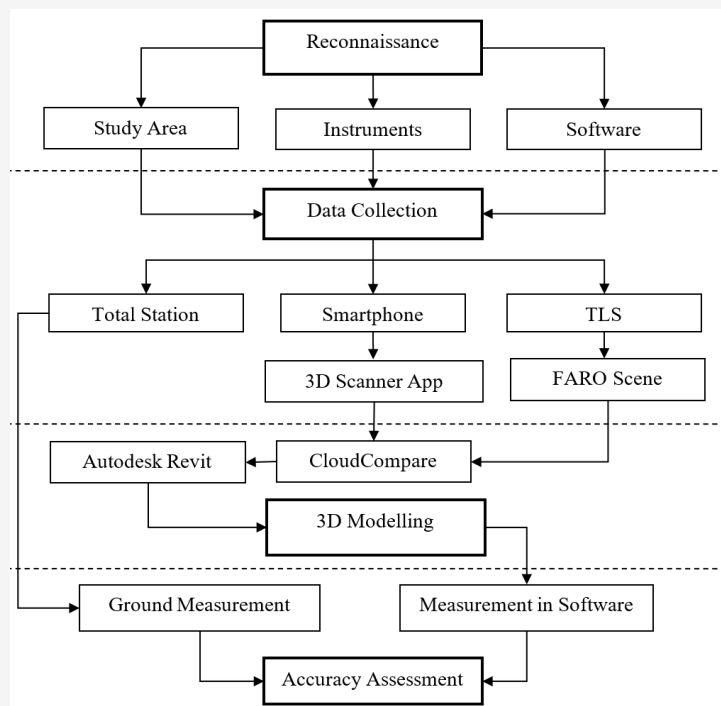


Figure 1: Enhancement of 3D modelling study workflow

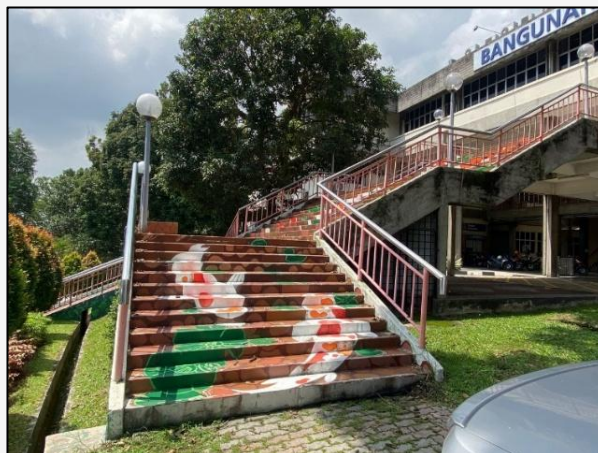


Figure 2: Stairs at Bangunan Wawasan

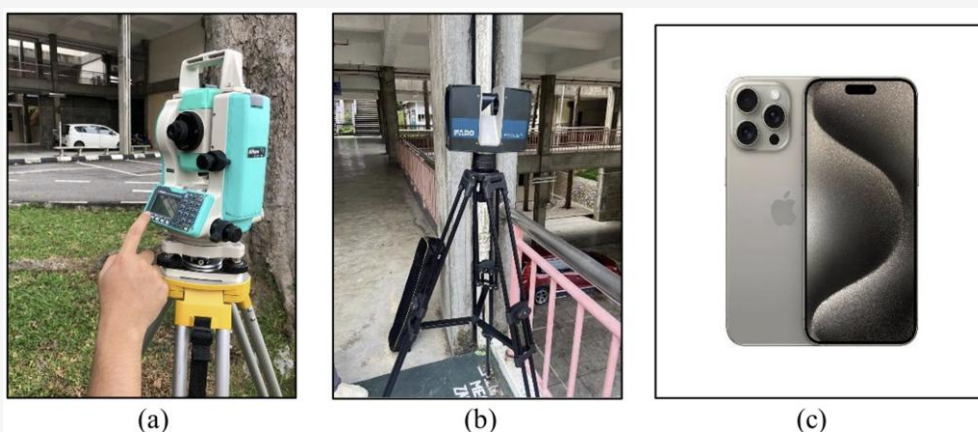


Figure 3: Instrument used (a) total station, (b) TLS, and (c) iphone 15 pro max

Meanwhile, the TLS and Smartphone LiDAR have been used to collect the 3D point clouds for the proposed approach. There were three types of software used in this study to process the point cloud data to produce the 3D model, and they are Faro Scene, CloudCompare and Autodesk Revit.

2.2 Instruments

There were three main instruments used in this study which are Total Station, TLS and iPhone 15 Pro Max. To achieve the objective of this study, the Total Station was used to collect the actual data for this study in terms of the dimensions of the buildings. Next, the TLS that was used in this study is the FARO Focus M70 Laser Scanner to do the overall scanning on this site. Lastly, for the uncovered area, the Smartphone LiDAR was used to scans the occluded area. The instrument is as shown in Figure 3.

2.3 Data Acquisition

In this study, two types of data were collected which

are 3D point clouds from TLS and smartphone LiDAR and benchmarking ground measurements from a Total Station. For ground measurements, a reference point (datum) was established using the CHC i80 device with static and RTK methods. According to circular of Department of Survey and Mapping Malaysia (DSMM) No. 3 2003 where the distance for Datum must more than 30m. The Total Station was set up on a tripod at a control point, and a reflector sheet was used to capture accurate building measurements. Traversing was conducted at four stations, and a DFT was performed beforehand to ensure instrument accuracy, with recalibration required if the error exceeded 10mm. The 3D point cloud data was obtained using TLS and Smartphone LiDAR. TLS scanned the entire building while Smartphone LiDAR was used for scanning hidden or hard-to-reach areas via the "3D Scanner App", which offers various scanning modes such as LiDAR and Point Cloud. The scanned data was exported in PTS format and processed in CloudCompare software.

2.4 Data Processing and Visualisation

During data processing, three software programs were used to handle the point clouds data efficiently. FARO SCENE was used for point cloud registration from multiple scan datasets to ensure proper alignment by linking common checkerboards and spheres. This software also had been used to perform georeferencing by assigning real-world coordinates obtained from the Total Station to the point clouds. Once the registration was completed, the processed data was imported into CloudCompare for further refinement. CloudCompare allowed for AI-Augmented for preprocessing, cleaning, and segmentation for the point cloud to improve accuracy and quality of the point clouds. The alignment process been done automatically by selecting corresponding reference points in both TLS and Smartphone LiDAR scans, which were labelled as "to be aligned entities" and "reference entities." The fused dataset was evaluated using the Root Mean Square (RMS) error. After alignment, the "Merge" tool in CloudCompare was used to combine the TLS and Smartphone LiDAR point clouds into a single and unified file which was then exported for 3D modelling. Then, the merged point cloud was imported into Autodesk Revit to reconstruct the 3D model of the building. Various structural components such as columns, beams, slabs, and railings were modelled based on the scanned point cloud data. Before initiating the modelling process, the point cloud was converted into a Recap (.rcp) file which is compatible with Autodesk Revit and ensures accurate dimensioning based on the scanned data. This processed 3D model was later used in the data analysis phase where its dimensions were quantitatively compared with benchmarking ground measurements to evaluate accuracy and consistency.

2.5 Data Analysis

The quantitative analysis was conducted in this study by comparing the measurements from 3D model with the benchmarking ground measurements using the RMSE equation 1, where x_i represented the length obtained from the total station measurement and x_0 represented the length from the 3D model.

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (x_i - x_0)^2}{n}}$$

Equation 1

Where:

x_i = predicted value

x_0 = observed value (actual measurement)

n = number of observation

3. Results And Discussion

In this study, the 3D model was developed based on point cloud data scans by TLS and the fused point cloud from TLS and Smartphone LiDAR. TLS provided high-resolution and precise spatial data with minimal noise, while Smartphone LiDAR offered flexibility in capturing data from areas that were difficult to access. The raw point clouds were processed to remove noise and redundant points. The datasets from both methods were then fused to generate full coverage of the staircase. The point clouds from TLS and Smartphone LiDAR are shown in Figure 4.

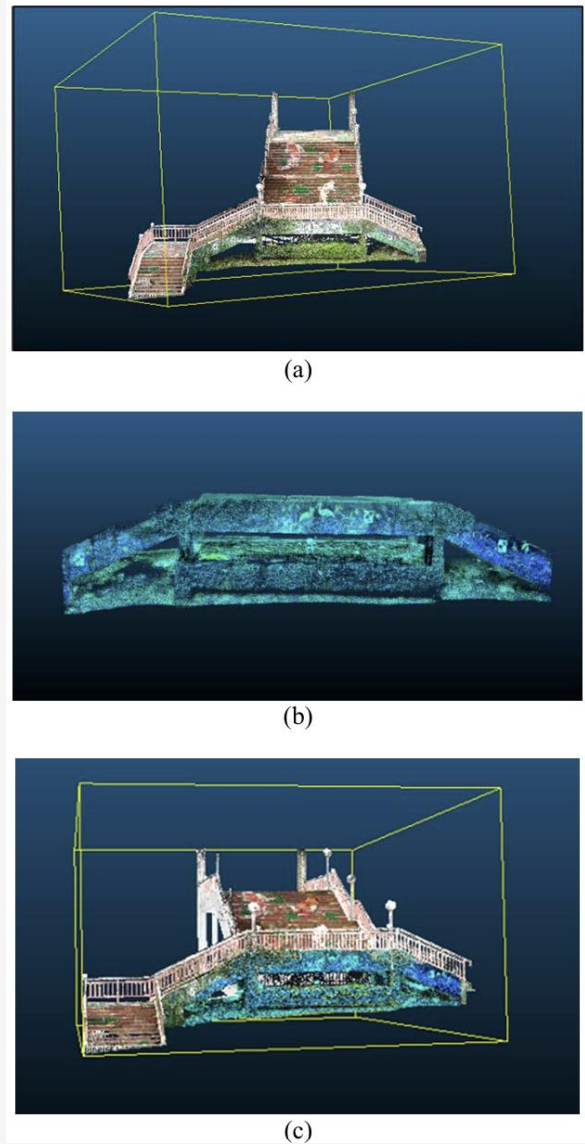


Figure 4: Point Cloud Data: (a) TLS, (b) smartphone LiDAR, and (c) fused point cloud

Based on the results of point cloud, it shows that the smartphone LiDAR can help in terms of data completeness, where it can cover the areas that cannot be accessed by TLS. Figure 5 shows the 3D model for these two types of point cloud data and the number of point cloud. To The integration of smartphone LiDAR extended the spatial coverage, particularly under staircases and in narrow corridors, as demonstrated by the increase in point cloud density from 5.7 million (TLS) to 7.1 million (Fused)

points. AI-based alignment achieved an RMS error of 0.008m, ensuring consistency during fusion. The final 3D models accurately represented the study area, ensuring better visualization and analysis for further evaluation. Therefore, a comparison between the models and actual measurements was calculated and evaluated as shown in Figure 6. The dimension error analysis evaluated the accuracy of the 3D models by comparing 30 measurement points from the TLS dataset and the fused dataset.

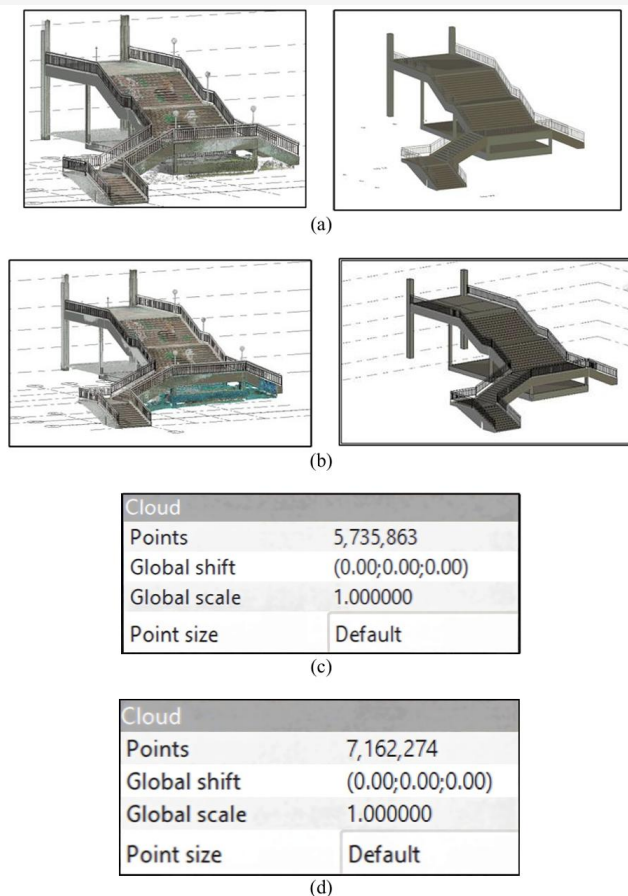


Figure 5: 3D Model: (a) 3D Model based on TLS Point Cloud, (b) 3D Model based on Fused Point Cloud, (c) Point Cloud Number before Fusing, (d) Point Cloud Number after Fusion

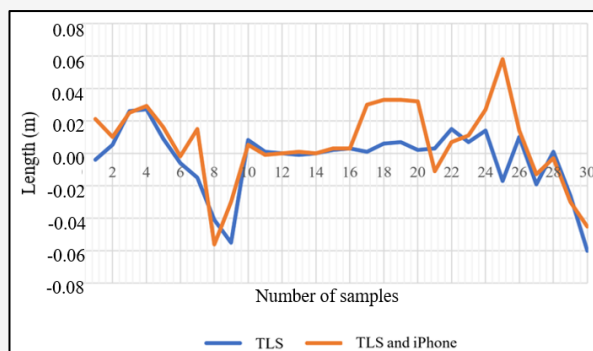


Figure 6: Error Value for TLS alone and merged in term of dimension

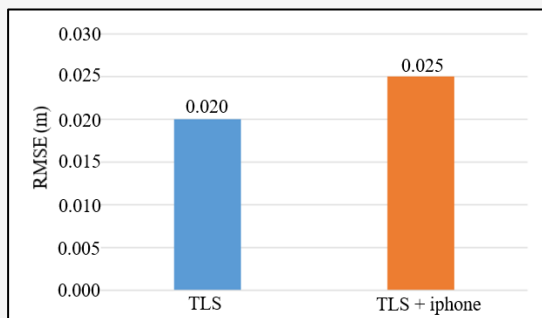


Figure 7: RMSE of TLS and Fused Point Cloud Data

A line graph illustrated the dimensional difference errors for each point, showing that the TLS dataset maintained a consistent error range of $\pm 0.030\text{m}$, while the merged dataset exhibited fluctuations, reaching up to $\pm 0.058\text{m}$ at Dimension 25. However, some dimensions show perfect alignment with a 0.000m difference in both datasets. The highest errors were recorded at Dimension 30 for TLS (-0.060m) and Dimension 25 for the fused dataset (0.058m). These variations indicate that while fusing TLS and Smartphone LiDAR data enhances coverage, it may introduce slight inconsistencies in certain areas. This shows that the TLS point cloud has the best accuracy rather than the fused point cloud, as it has a lot of lower values of error, which makes the RMSE value become lower. From the error values of the dimensions, RMSE can be calculated by using equation (1). In this study, the comparison of RMSE values for both models is shown in Figure 7 to assess the accuracy of the fused point cloud, which combined TLS and Smartphone LiDAR data and was compared with actual measurements.

The RMSE for the fused dataset was 0.025m , which was slightly higher than the RMSE for TLS alone, indicating minor additional errors introduced during the fusing process. The highest deviation in the fused dataset was 0.058m at Point 25, while multiple points showed no deviation (0.000m), which demonstrates perfect alignment. The bar chart comparison of RMSE values for TLS and the fused dataset, as shown in Figure 7 confirmed that the TLS dataset had lower RMSE values, signifying greater precision in measurements directly obtained from TLS compared to the fused dataset. This analysis highlights that while fusing TLS and Smartphone LiDAR improves data coverage, it may introduce slight variations affecting overall accuracy. However, the finding proved that AI algorithms played a key role in minimizing misalignments and enhancing point cloud interoperability, thus maintaining near-identical RMSE.

4. Conclusion

In this study, the analysis compares the performance of TLS alone as well as the AI-Augmented integration of TLS and Smartphone LiDAR. The TLS dataset shows a high precision, which it has achieved a RMSE of 0.020m . The dimensional differences for TLS are consistently low, within $\pm 0.030\text{m}$. However, the largest error is -0.060m at Dimension 30. Moreover, scanning by using TLS alone also faces a few limitations, especially in accessing complex areas, where it can reduce the overall spatial coverage. While the fused dataset that combines TLS and Smartphone LiDAR can achieve an RMSE of 0.025m , which is much higher than TLS alone. From the fused datasets, it shows a greater fluctuation in dimensional differences, where the largest error is 0.058m in Dimension 25. In addition, it also successfully captures an additional detail in areas that are inaccessible for TLS, which can enhance the overall coverage and completeness of the 3D model. This study also shows the coordinate assessment, which represents the difference of axes (X, Y, Z) for each point cloud and actual measurements. As a conclusion, while TLS remains superior in terms of accuracy, AI-supported smartphone LiDAR significantly enhances spatial coverage and detail, especially in occluded or constrained environments. However, there were several suggestions for the improvement of Smartphone LiDAR scans. First, the scanning technique should be considered to get a good dataset for the point cloud outcome. Second, the improvement of fusing techniques also plays a big role in the study. The mismatches in alignment or overlapping data can occur and could lead to reduced accuracy in the final 3D model.

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