Evaluating the Accuracy and Completeness of the 3D Building Model from Laplacian Method of Point Cloud Data Fusion

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Abstract

LiDAR and photogrammetry technologies generate point clouds that serve as a vital source of high-resolution spatial data for accurately reconstructing 3D building models. Along with these advancements, challenges such as occlusions and inconsistencies within individual datasets often lead to incomplete models, resulting in missing structural elements of the building, such as roof sections. The integration methods of multiple point cloud, known as data fusion, enhances data accuracy and completeness by complementing each dataset and addressing these issues. Among these techniques, Iterative Closest Point (ICP) is widely employed for point cloud registration, yet it does not fully eliminate gaps and redundancies. To overcome these limitations, the Laplacian method has been introduced, to refine alignment between point clouds, significantly enhancing overall accuracy and completeness. Despite advancements in point cloud fusion, evaluating the accuracy and completeness of the resulting models remains crucial to ensure their reliability and applicability. Research has shown that higher accuracy and greater point cloud density lead to improved reconstruction quality. This study focuses on evaluating the accuracy and completeness of 3D building models generated through point cloud fusion. Evaluation of the quality of 3D building models involves both qualitative methods, such as visual inspection, and quantitative metrics to measure geometric accuracy and structural integrity. The findings provide valuable insights into the reliability of current modelling techniques, contributing to quality control improvements and advancements in 3D reconstruction methodologies.

Keywords: Evaluation, Accuracy, Completeness, 3D building model, Point cloud, Data fusion.

1. Introduction

Point clouds, acquired through technologies such as LiDAR and photogrammetry, provide high-resolution spatial information for reconstructing complex structures of building object. However, limitations and occlusions of each technology make it difficult to obtain an accurate and complete 3D building model (Abdelazeem et al, 2021). Thus, a 3D building model generated from a single point cloud may be exhibiting holes or voids, such as a missing roof section (Mutiarasari et al., 2023). To address the issue, data fusion techniques integrate multiple point cloud sources, enhancing the overall quality (accuracy and completeness) of the 3D building models.

According to Adamopoulos & Rinaudo (2021), there are four types of fusion approaches for multi-source point cloud registration by using photogrammetric and ranging techniques: 1) manual annotation of common features, 2) iterative closest point – ICP, 3) feature-based, and 4) georeferencing-based. ICP is one of the most widely used approaches for data registration due to its simplicity, ease of use, and ability to deliver highly accurate results. However, following ICP registration, the fused 3D models are not yet accurate and complete as reported by Li et al. (2018) and Li et al. (2021). They identified that the fused 3D models exhibit stratified redundancies and gaps within interconnected regions. To address the issue, the Laplacian method was introduced by the latter work, outperforming other approaches such as curvature-based and volumetric fusion methods in enhancing the quality of fused 3D models. This method detects holes or voids in the 3D model and extracts source data to fill these holes in the target model, effectively eliminating stratified redundancies. Additionally, point migration is applied to minimize the gaps between the two point clouds. As a result, the Laplacian method enhances both the accuracy and completeness of the fused 3D models.

Higher-quality fused 3D models enable the generation of more accurate and complete 3D models, including those used for building reconstruction. Koshelham et al. (2021) confirmed that reconstruction quality improves when higher accuracy and more complete point cloud data are utilised. They evaluated 11 submitted models from different research teams, comparing each against manually generated reference models to assess geometric accuracy. Despite advancements in point cloud fusion, assessing the accuracy and completeness of the resulting models remains crucial to ensure their reliability and applicability.

Quality evaluation of 3D model from data integration has been demonstrated by researchers such as Murtiyoso et al. (2018) and Maset et al. (2022). They assessed the quality of 3D models based on geometric accuracy and completeness using a combination of qualitative and quantitative methods. The qualitative approach focusses on visual inspection and structural assessment, while the quantitative approach relies on numerical metrics. Qualitative evaluation complements quantitative analysis to ensure the 3D model is both geometrically accurate and visually realistic. For 3D building models, accuracy evaluation verifies alignment with real-world structures, while completeness assessment ensures that all essential features are captured.

Recent work on point cloud data fusion by Mutiarasari and Abdul Rahman (2025) applied Laplacian method to enhance the 3D building model. However, it has not presented a quality evaluation of their point cloud model. This paper focuses on

This contribution has been peer-reviewed.

evaluating the accuracy and completeness of the 3D building model from that point cloud data fusion. By systematically assessing this model, the study aims to provide insights into the reliability and limitations of current point cloud-based 3D modelling practices, contributing to quality control advancements and the improvements for future applications. In the end, this study utilises point cloud data fusion to generate 3D building model, demonstrating the potential of the enhanced 3D model as input for modelling purposes. The methodology of this study is detailed in Section 2, followed by the results and discussions in Section 3. Lastly, Section 4 presents the conclusion.

2. Methodology

2.1 Experimental Framework

This study conducts experiments to evaluate the fused 3D building model, with the framework illustrated in Figure 1. The evaluation examines two key aspects: accuracy, which measures its alignment with reference data, and completeness, which assesses whether the model captures all expected structures. The results are then analysed to assess the overall quality and reliability of the 3D building model. Finally, this study demonstrates how the fused 3D building model contributes to generating a 3D building model.

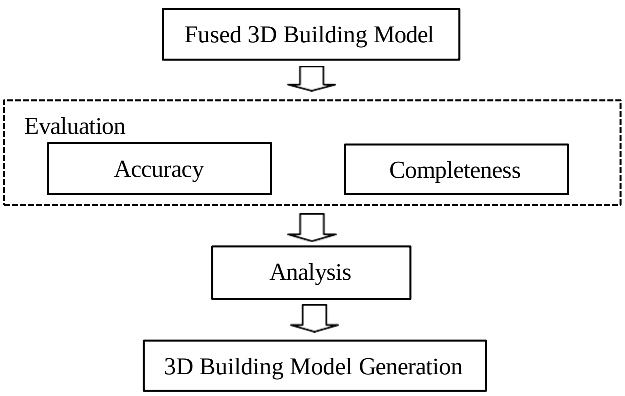

Figure 1. Framework of the experiments.

2.2 Data Fusion Enhancement: The Laplacian Method

The Laplacian method, introduced by Li et al. (2021), enhances 3D building models from integrated two sets of point clouds, achieving an average completeness of 82%. It consists of two stages: multi-view based 3D holes extraction and Laplacian data fusion. At the first stage, the target model (first point cloud) is observed from 37 viewpoints to identify the holes. The holes are identified when the number of points in the target falls below a specified threshold within the search window. Then, points from the source data (second point cloud) that overlap with the holes are extracted and reprojected into 3D. At the second stage, these points, used as substitute data, are computed for their differential coordinates and employed to guide the migration, effectively filling the holes.

Mutiarasari and Abdul Rahman (2025) reimplemented this approach, by generating an enhanced 3D building model of three sets of point clouds from terrestrial laser scanning (TLS), aerial laser scanning (ALS), and image-based photogrammetry, as shown in Figure 2. They used TLS-based model as reference data and applied ICP registration to align the ALS points and image-based points more closely with the reference. The study utilised Python programming to identify holes in the TLS model from a single viewpoint and extract the ALS points and image-based points to fill the holes. However, the quality of this model has not yet been assessed. Therefore, this study evaluates its accuracy and completeness to ensure its reliability. Specifically, the evaluation focuses on the accuracy of integrating the TLS model (target) with image-based points (source), as the image-based points provide a higher point density and exhibit more significant point migration.

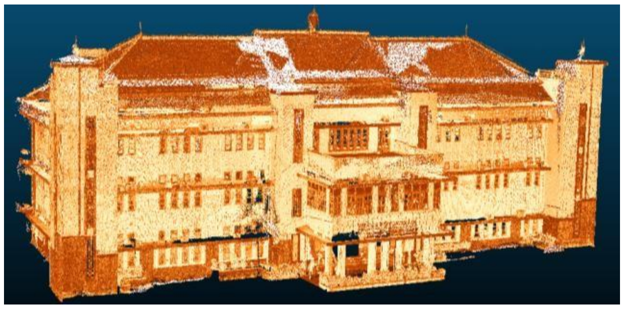

Figure 2. The fused 3D building model consists of TLS points in orange, UAV points and image-based points in white.

2.3 Accuracy

In this study, accuracy assessment is based on the performance of the Laplacian method and the enhanced 3D model. The Laplacian method focuses on point migration to minimize the gaps between point clouds, enhancing overall data integration. To evaluate its effectiveness, the mean distance between two point clouds before and after enhancement is used as a performance metric of this method.

$$d_{\text{mean}} = \frac{1}{N}\sum_{i=1}^{N} d_i \quad , \tag{1}$$

where d_{mean} = mean distance
N = total number of points in the reference
d_i = Euclidean distance

The mean distance is calculated by summing all individual Euclidean distance values (d_i) from i = 1 to N, where is N is the total number of distance values. Euclidean distance is a measure of the straight-line distance between two points, representing the length of the shortest path connecting them. The sum of d_i is then dividing the total by N, giving the average distance, denoted as d_{mean}.

Accuracy of the 3D models depend on various factors including the source data, complexity of the shapes, etc (Ostrowski et al., 2018). Usually, accuracy of the 3D model is calculated by comparing the model with reference model such as performed by Jarząbek-Rychard and Karpina (2016). For this 3D model, the evaluation of accuracy is conducted on parts of the target model that are filled by the source data, comparing them to the check points. In this case, check points are the references to evaluate the source data on the 3D model. This assessment measures how precisely the source data fills the holes in the target model. Check points are independently measured using high-accuracy methods, such as total stations, to verify the accuracy of survey or dataset. Some check points identified on a real building object are used to analyse the model's deviation.

The differences between the coordinates of the check points and the corresponding locations in the fused 3D building model are quantified using the Root Mean Square Error (RMSE), as shown in Equation 2.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}((\Delta X_i)^2 + (\Delta Y_i)^2 + (\Delta Z_i)^2)} \quad (2)$$

where N = total number of check point
X, Y, Z = 3D model and check point coordinates

RMSE is calculated by first computing the squared differences in the X, Y, and Z coordinates for each point. These squared differences are then summed for all points. The total is divided by N to obtain the mean squared error, and finally, the square root of this value is taken to obtain the RMSE.

In this study, building surfaces with large voids were chosen to be evaluated, specifically, 5 out of 10 building walls. The roof was excluded due to limitations in measuring check point coordinates. The number of points on each wall varied depending on the size of the voids, with 1 to 3 points selected for each void. Their locations were sketched to facilitate recognition during analysis.

2.4 Completeness

Completeness is used to evaluate whether the missing data on the 3D models is filled by the source data. In this study, the fused 3D building model is assessed based on qualitative and quantitative approaches. The qualitative approach involves visually examining the fused 3D building model to identify essential features of the object. This assessment focuses on determining whether key structural elements, such as walls, roofs, doors, and windows, are accurately represented in the model. This qualitative evaluation serves as a preliminary step before conducting quantitative completeness assessment.

For quantitative approach, completeness of the fused 3D building model is calculated as the percentage of holes resolved by source data as demonstrated by Li et al. (2021). A hole in the 3D model is considered resolved when it is fully or partially filled with points, while it is deemed unresolved if no points fill the void.

$$Completeness\ (\%) = \frac{Filled\ holes\ (H)}{Unfilled\ holes\ (h)}\ x\ 100\% \quad (3)$$

3. Results and Discussions

3.1 Accuracy: The Laplacian Method and the Fused 3D Building Model

In this study, the accuracy of the Laplacian method for enhancing the integrated point cloud is evaluated by calculating the mean distance, which reflects the gap between the two point clouds. Initially, the mean distance between the two point clouds was 56.5 cm, indicating a noticeable discrepancy. After applying the enhancement process, the mean distance decreased to 41.55 cm, demonstrating improved alignment and integration of the point clouds. A smaller mean distance signifies that the source points from image-based data are closer to the target TLS points, used as reference. This reduction suggests that the Laplacian method effectively minimizes gaps and enhances the overall spatial consistency of the fused 3D building model.

To further analyse the improvement in alignment, an investigation was conducted on 15 individual parts of the building, comprising five roof sections and ten wall sections. The mean distance for each part was calculated separately to assess the local accuracy of the enhancement process. The results are visually represented in a graph (Figure 3), highlighting the enhanced alignment achieved in different regions of the building model.

The bar graph compares the mean distance between different parts of a building before and after applying the Laplacian-based point migration. Overall, the green bars (after enhancement) are consistently lower than the orange bars (before enhancement), indicating that the enhancement process effectively reduced the mean distance and improved geometric accuracy across all building parts.

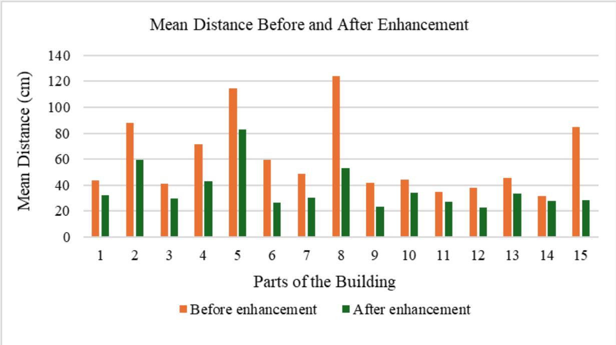

Figure 3. Comparison of mean distance between point clouds before and after enhancement.

The accuracy of the fused 3D building model is assessed by comparing check points with selected points in the model. The check points, derived from the actual building used in this study, correspond to specific areas in the target model that have been supplemented with source data. A total of 23 check points were accurately measured using a total station and used to calculate the coordinate differences (X and Y) relative to the corresponding points in the fused 3D building model. Both the 3D building model and the check points are represented in the same Cartesian coordinate system, ensuring consistency in the accuracy assessment. The results of the coordinate differences are presented in Table 1.

Points	Check Point		Difference	
	X (meter)	Y (meter)	ΔX	ΔY
111	431013.458	9140523.236	0.687	0.430
115	431017.896	9140520.726	0.603	0.024
116	431018.879	9140520.326	0.550	0.114
117	431021.522	9140519.250	0.062	0.131
118	431022.512	9140518.843	0.142	0.198
119	431023.418	9140518.483	0.038	0.198
122	431018.171	9140534.589	0.009	0.537
123	431017.647	9140533.332	0.103	0.644
124	431017.954	9140534.067	0.383	0.759
140	431011.024	9140559.440	0.062	0.291
141	431012.409	9140558.874	0.387	0.015
143	431012.724	9140558.803	0.692	0.044
144	431011.301	9140559.399	0.150	0.250

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146	431017.097	9140556.946	0.514	0.287
147	431016.190	9140557.319	0.581	0.400
148	431015.576	9140557.573	0.515	0.424
151	431019.460	9140555.973	0.278	0.144
154	431019.256	9140556.065	0.304	0.066
158	431027.601	9140557.526	0.006	0.338
161	431028.153	9140558.894	0.075	0.200
171	431038.134	9140567.250	0.753	0.192
172	431038.138	9140567.243	0.687	0.040
173	431037.309	9140567.576	0.858	0.136

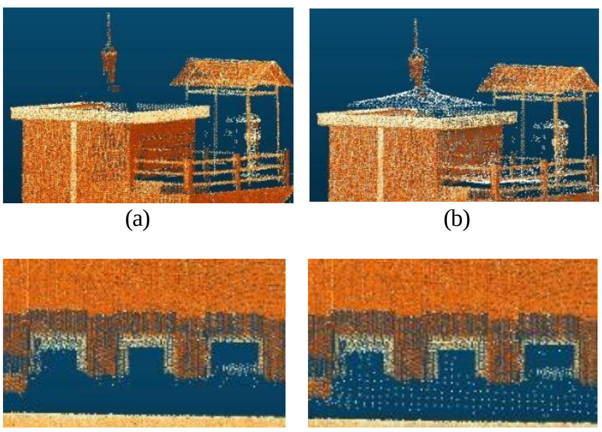
Table 1. Check points and their differences with the selected points in the fused 3D building model

This study evaluated the planimetric accuracy (X and Y coordinates) of the 3D building model. The differences in X and Y coordinates from Table 1 were used as input for Equation 2 to calculate the RMSE. Based on 23 check points, the RMSE was found to be 55.8 cm, indicating relatively low accuracy of the selected points in the building model. This inaccuracy may be attributed to the migrated points, which filled the target model with limited precision. Furthermore, the comparison stage between check points and selected model points could contribute to the error. The limited number of points in the model may lead to inaccurate position estimation, meaning that the selected points might not be precisely represented by the check points.

Both the accuracy of the Laplacian method and the fused 3D building model demonstrate limited performance. This level of accuracy is insufficient for the reliable representation of building objects. Further improvement is needed, particularly through enhanced processing technique, such as optimizing the parameters used in the Laplacian method, to achieve more accurate and realistic results.

3.2 Completeness: Qualitative and Quantitative Approaches

Visually, the enhanced 3D building model displays more complete structural elements. The original TLS model lacked certain rooftop details due to sensor's line of sight and exhibited holes in the walls due to shadows cast by vegetation. An example of this completion is illustrated in Figure 4.



(a) (b) (c) (d)

Figure 4. Building parts before integration (a and c) and after integration (b and d).

The original TLS model, shown in orange, is complemented by image-based points, represented in white. In Figure 4, missing rooftop details (a) and a hole in building wall (c) are filled in by the source data, as shown in (b) and (d).

Quantitatively, the completeness of the fused 3D building model is evaluated by comparing the number of filled and unfilled holes. Using Python, 200 filled holes and 31 unfilled holes were identified, resulting in a completeness percentage of 86.58%. Compared to the previous work by Li et al. (2021), the completeness is 4% higher as shown in Figure 5. This increase may be influenced by factors such as more complete input data and the values of parameters set in the programming code. Since this is ongoing research, the completeness may be further improved by modifying the Laplacian method.

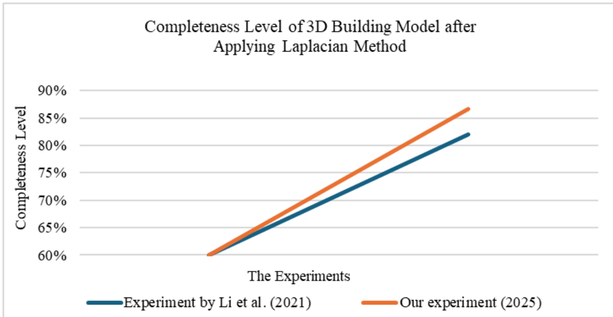


Figure 5. Comparison of the fused 3D building model completeness with Li et al. (2021).

3.3 Generated 3D Building Model

The 3D building model generated from fused point cloud is processed to generate a simplified 3D building model using a RANSAC-based approach. RANSAC algorithm is applied to extract planar surfaces from the point cloud, enabling the reconstruction of key building elements such as roofs and walls. This study focuses on simple 3D building model; therefore, it excludes non-planar shapes like spheres, torus structures, and other complex geometries. The detected planar surfaces are then used to construct a surface mesh, forming a simplified representation of the building. This 3D model generation is processed using Python and includes two main stages: plane detection and mesh reconstruction. Algorithm of the plane detection and reconstruction planes to mesh are presented in Figure 6 and Figure 7.

```
Algorithm: Plane Detection
procedure DETECT_PLANES(points, threshold, min_ratio, min_fixed, voxel_size,
   merge_th, norm_radius)
  pcd ← convert_to_pointcloud(points),estimate_normals(pcd, norm_radius)
  downsampled_points, downsampled_normals ← voxel_downsample(pcd, voxel_size)
  min_points ← max(min_ratio × size(downsampled_points), min_fixed)
  planes, remaining_points, remaining_normals ← [], downsampled_points,
  downsampled_normals
  while size(remaining_points) > min_points do
      best_eq, inliers ← RANSAC(remaining_points, threshold)
      if size(inliers) < min_points then break
      normal ← normalize(mean(remaining_normals[inliers], axis=0))
      if not merge_plane(planes, best_eq, normal, remaining_points[inliers], merge_th)
      then
          append(planes, (best_eq, remaining_points[inliers]))
      remove_inliers(remaining_points, remaining_normals, inliers)
  return planes
end procedure
```

Figure 6. Algorithm for planar surface detection.

```
Algorithm: Reconstruct Planes to Mesh
procedure RECONSTRUCT_PLANES_TO_MESH(planes)
  meshes ← []
  for each (plane_eq, inlier_points) in planes do
      if size(inlier_points) < 3 then continue
      pcd ← convert_to_pointcloud(inlier_points)
      hull ← compute_convex_hull(pcd), orient_triangles(hull)
      append(meshes, hull)
  return meshes
end procedure
```

Figure 7. Algorithm for planes to mesh reconstruction.

The plane detection algorithm operates by iteratively extracting planar regions from a 3D point cloud using a RANSAC-based approach. Initially, the input point cloud is converted into a structured format, and surface normals are estimated using a specified neighborhood radius. To enhance computational efficiency and reduce noise, the point cloud is down sampled using a voxel grid, producing a sparser set of points and their corresponding normals. A minimum inlier threshold is then calculated based on a fixed value and a user-defined ratio of the down sampled points. The algorithm proceeds by repeatedly applying RANSAC to the remaining points to detect the most dominant plane in the scene. If the number of inliers found by RANSAC falls below the threshold, the process terminates. Otherwise, the average normal of the inlier set is computed, and the detected plane is compared against previously found planes to check for redundancy using a merge threshold. If it is considered a new plane, it is stored along with its inliers, and those inliers are removed from the remaining point set. This process continues until no significant planes can be identified, at which point the algorithm returns the set of detected planes. This method ensures efficient and robust extraction of multiple planar surfaces from noisy 3D data.

The mesh reconstruction algorithm transforms a set of detected planar segments into a collection of 3D mesh surfaces. It operates by iterating through each plane, represented by its equation and associated inlier points. For each set of inliers, the algorithm first verifies that there are at least three points, as this is the minimum requirement for forming a valid polygon. The inlier points are then converted into a point cloud structure. Using this representation, a convex hull is computed to approximate the boundary of the planar region. The resulting polygon is further processed to ensure consistent triangle orientation, which is important for proper rendering and mesh integrity. Each generated mesh is stored in a list, which is returned upon completion of the process. This approach provides a simple yet effective means of converting planar point sets into closed mesh representations, suitable for visualization or further geometric analysis. The execution of these algorithms produces a mesh model of the 3D building object, as shown in Figure 8.

Figure 8. Mesh model of the building object.

The mesh model represents major building elements such as roofs and walls but lacks windows, doors, and other detailed architectural features. The surfaces of the mesh are relatively rough, resulting in a simplified and non-realistic building shape. Additionally, some parts of the model, such as wall corners, are not properly connected. This is due to the separate mesh reconstruction process applied to each building part.

4. Conclusion

Application of the Laplacian method significantly improved the alignment and spatial consistency of 3D building model generated from data fusion. The reduction of the gaps indicates the enhanced integration and accuracy. Furthermore, the enhancement was consistently effective across different sections of the model. However, it is noted that the accuracy is still limited. Further refinements using parameters adjustment, such as density threshold and boundary threshold, could potentially optimize the model even further, ensuring greater precision and completeness in the future applications.
Additionally, the enhanced data fusion has the potential to generate a mesh-based 3D building model. However, the resulting model remains simplified, capturing only major components such as roofs and walls, while lacking finer details like doors and windows. Generating 3D models from point clouds presents its own challenges, primarily due to the high level of noise inherent in the data. To achieve a more accurate representation, further processing is strongly recommended, such as converting the model into a solid model that can reflect the Level of Detail (LoD) of the building. Consequently, the final 3D building model output, such as CityGML, will be explored further.

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