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Improving Surface Strip Adjustment Accuracy Using the Point-to-Plane Iterative Closest Point (ICP)

Improving Surface Strip Adjustment Accuracy Using the Point-to-Plane Iterative Closest Point (ICP) Algorithm

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Abstrak: Penelitian ini bertujuan mengevaluasi efektivitas metode *point-to-plane* untuk registrasi data *point cloud* LiDAR, khususnya untuk aplikasi *strip adjustment*. Dengan menggunakan dua *scene* LiDAR yang berbeda dengan tutupan lahan yang bervariasi, analisis komparatif dilakukan antara metode *point-to-plane* dan metode konvensional *point-to-point*. Kinerja metode *point-to-plane* dinilai berdasarkan *Root Mean Square Error* (RMSE), akurasi matriks transformasi, *fitness*, korespondensi, dan pengamatan visual. Hasilnya menunjukkan bahwa metode *point-to-plane* secara konsisten mengungguli pendekatan *point-to-point*, dengan menghasilkan nilai RMSE yang jauh lebih rendah, matriks transformasi yang lebih akurat, dan skor *fitness* yang lebih tinggi di semua jenis tutupan lahan. Studi ini memvalidasi bahwa ICP *point-to-plane* mampu memberikan hasil yang lebih kuat dan akurat untuk registrasi data topografis, serta menawarkan peningkatan pada aplikasi geospasial berpresisi tinggi.

Abstract: *This study aims to evaluate the effectiveness of the point-to-plane method for LiDAR point cloud data registration, especially for strip adjustment applications. Using two different LiDAR scenes with varying land cover, a comparative analysis was conducted between the point-to-plane method and the conventional point-to-point method. The performance of the point-to-plane method was assessed based on Root Mean Square Error (RMSE), transformation matrix accuracy, fitness, correspondence, and visual observation. The results show that the point-to-plane method consistently outperforms the point-to-point approach, by producing significantly lower RMSE values, more accurate transformation matrices, and higher fitness scores across all land cover types. This study validates that point-to-plane ICP is capable of providing more robust and accurate results for topographic data registration, and offers improvements to high-precision geospatial applications.*

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INTRODUCTION

LiDAR technology has emerged as a powerful mapping and spatial analysis tool, primarily due to its unparalleled vertical accuracy in capturing three-dimensional spatial data. This precision is particularly beneficial in various applications, including 3D scene reconstruction, urban planning, and environmental monitoring, especially in complex environments such as underground tunnels, where accurate measurements are paramount (Gökgöz & M. Baker, 2015; Lin, Wang, & Nan, 2024; Wu, Shen, & Li, 2022). The elevation models generated from LiDAR data can achieve remarkable map accuracy at a scale of 1:1,000, owing to LiDAR's high resolution and ability to record numerous coordinates of objects on the Earth's surface with centimetre-level precision (Cao et al., 2023; Gökgöz & M. Baker, 2015; Lin et al., 2024; Silva-Fragoso, Norini, Nappi, Groppelli, & Michetti, 2024; Wu et al., 2022; Yoshida & Koarai, 2024). Such high-quality elevation models provide a robust foundation for various analytical tasks, facilitating more effective decision-making processes across multiple fields.

To ensure that this high level of accuracy is maintained, it is essential to manage LiDAR outputs meticulously at every stage of the workflow (H. P. Chen, Chang, & Liu, 2012; Z. Chen, Li, & Yang, 2021; Dhruwa & Garg, 2023). A critical challenge in working with point clouds, particularly when combining data from multiple scans or different viewpoints, is the need to align them into a single, cohesive coordinate system. This process is formally known as strip adjustment. Effective strip adjustment is indispensable for reconstructing complete 3D scenes, integrating disparate scans without introducing gaps, deformations, or outliers, and enabling accurate spatial analysis. Consequently, registration stands as a pivotal step for numerous downstream tasks, including comprehensive 3D reconstruction, precise map building, and robust localization in complex environments.

The Iterative Closest Point (ICP) algorithm has gained considerable attention. This method identifies intersection points on surfaces between corresponding points and their intended targets (S. Chen, Nan, Xia, Zhao, & Wonka, 2019). Empirical studies have shown that the point-to-plane method significantly improves the registration accuracy for point cloud datasets, particularly for non-topographic objects, while reducing the time required for these processes (Kuçak, Erol, & Erol, 2022; Liang & Pei, 2023; Saleh & Momeni, 2024; Zhang, Yao, & Deng, 2021). One of the primary reasons the point-to-plane method can enhance accuracy is its sensitivity to surface orientation (Zhang et al., 2021). In surface alignment tasks, the normal vectors of surfaces play a crucial role in determining how well the points can be matched. Considering these, the normal point-to-plane method is better equipped to capture surface variations that may go undetected using the traditional point-to-point method (Hexsel, Vhavle, & Chen, 2022; Kuçak et al., 2022; C. Lv, Lin, & Zhao, 2023). This capability not only reduces errors caused by noise but also enhances convergence toward more optimal solutions. Moreover, in the context of processing large point cloud datasets, the point-to-plane method reduces the number of iterations required to achieve convergence. The adjustment process can be executed more swiftly and efficiently by leveraging surface information (W. Lv, Zhang, Chen, Li, & Sang, 2024; Yue et al., 2022). This advantage is particularly critical in real-time applications or when handling extensive datasets, where processing time becomes a significant concern (Favre, Pressigout, Marchand, & Morin, 2021; Xu, Qin, & Song, 2023).

Despite its proven effectiveness in non-topographic applications, the point-to-plane method has not been extensively explored for its ability to register topographic features on the Earth's surface. This research gap presents a critical opportunity to examine the reliability and applicability of the point-to-plane method in real-world geospatial scenarios. Therefore, this study is designed to systematically evaluate the effectiveness of the point-to-plane method for registering LiDAR point cloud data that represents topographic surfaces, with a particular focus on its implementation in strip adjustments. To achieve this, a comparative analysis will be conducted between the point-to-plane method and the conventional point-to-point registration technique. The performance of each method will be assessed using quantitative metrics, such as the root mean square error (RMSE) and fitness values, alongside qualitative visual assessments to determine its reliability across various types of land cover. Ultimately, this investigation seeks to provide empirical evidence to support the adoption of the point-to-plane method in standard workflows for topographic surveys. By demonstrating its potential to enhance registration accuracy, the findings could significantly improve the reliability of derived geospatial products, such as digital elevation models (DEMs) and change detection analyses.

METHOD

The initial phase of the workflow is dedicated to the foundational steps and preliminary preparation, which are critical for the subsequent success of the registration process. The second phase is dedicated to the implementation of the core registration algorithm and its subsequent rigorous validation. The effectiveness and reliability of the point cloud registration process are rigorously assessed through a combination of quantitative metrics and qualitative visualization. This multi-faceted approach ensures a comprehensive understanding of the algorithm's performance. The concluding phase of the workflow involves a thorough assessment of the registered point cloud, leading to comprehensive insights and conclusions. All of the processes can be seen in Figure 1.

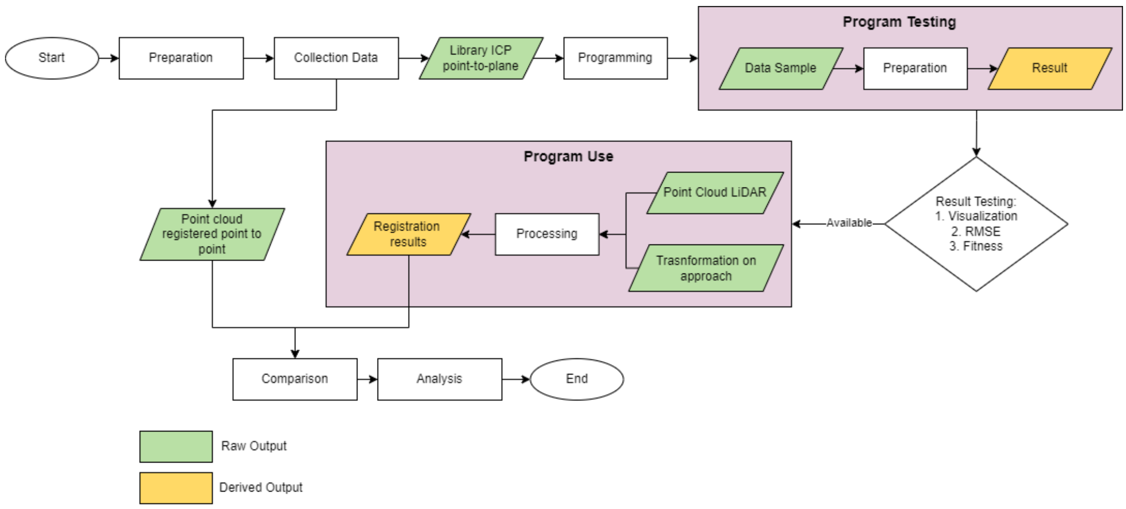


Figure 1. Research Workflow

Preparation and Data Collection

The data used in this research are two overlapping point cloud datasets that represent various types of land use found on the Earth's surface (Figure 2). The land cover includes paved roads and pathways, buildings, dense vegetation, low vegetation, and open land. The data collected is limited to the area of Scene 1, indicated by the yellow boundary, and the area of Scene 2, indicated by the blue boundary. The information for each data point can be seen in Table 1. The overlap results from each scene are presented in Figure 3.

Table 1
Information of the Point Cloud

No	Parameter	Data Scene 1	Data Scene 2
1	ID	Flight 1_1 – Cloud – 1	Flight 1_2 – Cloud – 2
2	Format	.las	.las
3	File size	9.4 MegaByte	9.7 MegaByte
4	Number of Point Clouds	705,852 points	715,181 points
5	Point Density	37.588 point/m2	36.735 point/m2
6	Point Spacing	0.163 meters	0.165 meters

Source: Data Processed

Figure 2. Research Location

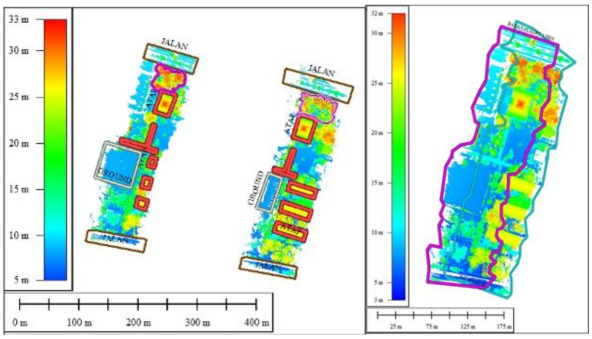


Figure 3. The Point Cloud Representation of Each Scene Overlaps with One Another

The trajectory data had been proceed by Trajectory Processing module on the mdInfinity platform. This process commenced with the processing of raw Global Navigation Satellite System (GNSS) data, which was validated with corrections from a ground base station. Subsequently, the processed GNSS data was hybridized with data from the Inertial Measurement Unit (IMU) to generate a final, smoothed trajectory. The output of this stage is an Exterior Orientation (EO) file in SBET format, projected into the designated coordinate system and ready for the georeferencing of the LiDAR point cloud.

The performance of the Iterative Closest Point (ICP) algorithm, which forms the core of this workflow, is notably sensitive to the initial quality of the data. A suboptimal initial alignment or noisy input data can lead the ICP algorithm to converge to a local minimum or, in severe cases, fail to converge altogether. Therefore, the reparation step, beyond merely setting up data collection, implicitly incorporates crucial pre-processing techniques. These techniques, which may include denoising and outlier removal, are not just best practices but are fundamental to providing clean, manageable data. Such robust pre-processing facilitates a more accurate and stable initial guess for the ICP algorithm, thereby significantly improving its convergence speed, overall accuracy, and computational efficiency. The thoroughness of this initial data preparation is a critical enabler for the success of the entire registration pipeline, mitigating potential issues before the core algorithm is applied.

Algorithm Development and Testing

The central component of this workflow is the development and implementation of the Iterative Closest Point (ICP) algorithm, specifically its point-to-plane variant, as depicted by the library ICP point-to-plane in the flowchart. The fundamental principle of ICP involves iteratively refining the spatial alignment between a source point cloud and a target point cloud. This is achieved by establishing correspondences between points in the two clouds and then computing a rigid transformation (comprising rotation and translation) that minimizes the distances between these correspondences.

The process of collecting libraries for program development begins with the installation of the Python programming language. The purpose of this installation is to provide an environment for running the libraries that will be used in this research. After all the required library packages have been collected and installed, the strip adjustment program is run using the Iterative Closest Point (ICP) algorithm with the point-to-plane method, where all its functions can be retrieved from the installed Open3D package library. To ensure that the program that has been made can run properly and is by the rules for making the program, it is necessary to carry out a program validation process before the program is run to carry out strip adjustment work. In this study, the program validation process is carried out by entering training data that has been prepared by the library documentation, where the data can be ascertained to be ideal and normal for validating the program. In this study, a program was developed to address the lack of a command for exporting the results of strip adjustment. This study modifies the existing command to facilitate this functionality.

To execute the Iterative Closest Point (ICP) algorithm, two datasets are required: the source point cloud and the target point cloud. Each iteration of the ICP algorithm begins by establishing a set of correspondences between points in the source and target point clouds. For example, the nearest point in the target point cloud is selected as the correspondence for each point in the source point cloud (Besl & McKay, 1992) with alternative approaches for finding correspondences discussed by Rusinkiewicz & Levoy(Rusinkiewicz & Levoy, 2001). The result of the ICP iterations is a precise 3D transformation value based on the source point cloud matrix, minimizing the total error between corresponding points to a predefined minimum threshold. When using the point-to-plane error matrix, the objective of minimization is the sum of squared distances between each source point and the tangent plane at the corresponding target point (Baek, 2020) (Figure 4).

The point-to-plane variant of ICP distinguishes itself from the more basic point-to-point ICP. While point-to-point ICP minimizes direct Euclidean distances between corresponding points, the point-to-plane approach minimizes the distance from each source point to the tangent plane at its corresponding target point. This method necessitates the estimation of surface normal for the target point cloud, and sometimes for the source cloud as well. The strategic selection of the point-to-plane variant is a deliberate technical choice, indicative of an informed design decision. This variant is often favoured due to its demonstrated advantages, including faster convergence speed and higher accuracy, particularly when processing scenes that contain significant planar or structured surfaces. This enhanced performance stems from its ability to more effectively leverage the underlying surface geometry, providing a more robust and efficient optimization process compared to its point-to-point counterpart. The program testing block is the systematic validation phase for the implemented ICP algorithm. This phase is crucial for ensuring the algorithm's robustness and accuracy before its operational deployment.

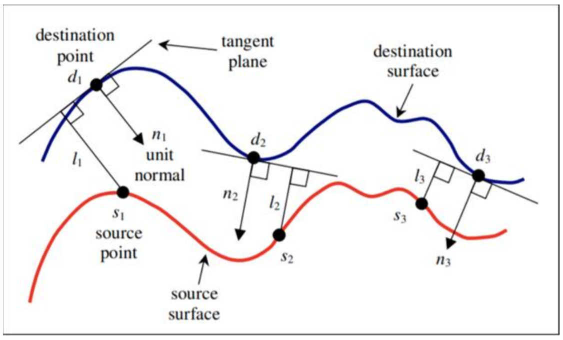


Figure 4. Point-to-plane projection distance
Source: Baek, 2020

Initially, a representative "Data Sample" is selected. These datasets are specifically chosen to test the algorithm's performance across a variety of scenarios and complexities, allowing for a thorough evaluation of its robustness under different conditions. The preparation step within this testing phase involves setting up the test environment, meticulously defining specific test cases, and, where feasible, establishing ground truth transformations. These ground truths serve as a reliable benchmark against which the algorithm's computed output can be quantitatively compared, providing an objective measure of its accuracy. The result of this testing process represents the raw output generated by executing the ICP algorithm on the selected test data.

Data Processing

LiDAR point cloud data is subjected to processing, where a point-to-plane ICP algorithm is implemented. This involves iterative steps to find correspondences and compute the optimal rigid transformation aligning the input point clouds. The spatial registration between the source and target point clouds is defined by a 4x4 homogeneous transformation matrix, which encapsulates a 3x3 rotation matrix (R) and a 3x1 translation vector (t). The optimal transformation was determined using the Iterative Closest Point (ICP) algorithm. A critical prerequisite for accurate alignment is a close initial transformation estimate. To satisfy this, the initial transformation (trans_init) was calculated directly from the sensor's pose information. The subsequent ICP refinement employed a correspondence distance threshold **of 0.5 meters**. This value was selected to robustly filter outliers during the iterative process without incorrectly discarding valid point pairs, ensuring the final alignment's precision.

The registration results, consisting of calculated transformation matrices and potential quality indicators, are then used to physically align the source point cloud to the target point cloud. This transformational approach effectively integrates the disparate point clouds into a shared coordinate system. Figure 5 shows the results of the strip adjustment using the point-to-plane registration method, which was carried out in the program that was created.

The main comparison was made on the results of point cloud scene data (Figure 6) processing, which was processed using the point-to-point registration method, with the results from the point-to-plane registration method. The point-to-point registration result made by CloudCompare produces overlapping transformation values of the approach and point cloud scenes. The results of the two methods are compared regarding the root mean square error value, fitness, and visual appearance of the strip adjustment results, whether the patch is suitable, or there are still deficiencies. In addition, an analysis of the program's performance in implementing the registration method is also carried out by analysing the registration results for each specific object that has been determined: roofs, roads, vegetation, and ground.

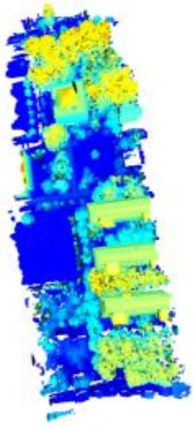


Figure 5. Point cloud scene data from point-to-plane.

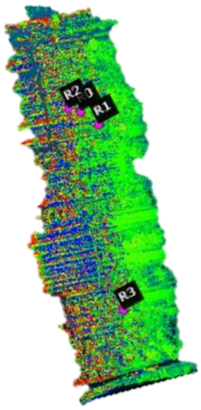


Figure 6. Point cloud scene data from point-to-point.

Comparison

A crucial qualitative assessment involves the visual inspection of the aligned point clouds. This provides an immediate and intuitive understanding of the registration quality. A successful alignment is typically characterized by a tight and seamless overlap between the source and target point clouds. A greater and tighter overlap visually confirms a superior alignment result.

Quantitative assessment involves the quality of the result by the value (Table 2). Root Mean Square Error (RMSE) is a widely recognized quantitative metric used in point cloud registration to precisely measure the accuracy of the alignment. It quantifies the average Euclidean distance between the aligned points of the transformed source point cloud and their closest corresponding points in the target point cloud.

The fitness score is another critical quantitative metric that offers valuable insight into the degree of spatial overlap achieved between the registered point clouds. It is computed as the ratio of the number of inlier correspondences to the total number of points in the target point cloud. A higher fitness score directly correlates with a greater overlapping area, thereby indicating a more successful registration in terms of coverage and completeness.

Table 2
Key Evaluation Metrics for Point Cloud Registration

Metric	Definition	What it Measures	Interpretation
Root Mean Square Error (RMSE)	The square root of the average of the squared differences between the Euclidean distances of aligned points.	The accuracy of the geometric alignment between the transformed source point cloud and the target point cloud.	Lower values indicate higher accuracy and precision in registration.
Fitness Score	The ratio of the number of inlier correspondences to the total number of points in the target point cloud.	The degree of overlapping area between the registered point clouds.	Higher values indicate greater overlap and more successful registration in terms of coverage.

Source: Data Processed

Table 3
Comparison of Point- to-Point and Point-to-Plane Adjustment Strip Results

No	Parameter	Result Point to Point	Result Point to Plane
1	Root Mean Square Error Value	8.71 centimeters	1.53 centimeters
2	Transformasi Value	Small rotation value, Large translation value	Small rotation value, Large translation value
3	Fitness Value and Correspondence	No Information	0.001 and 1054

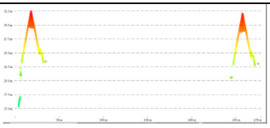
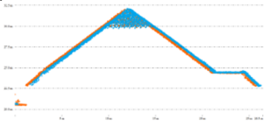
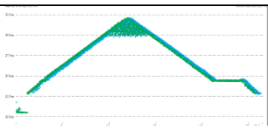
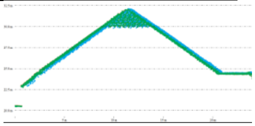
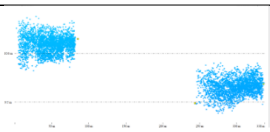
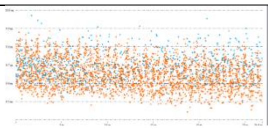
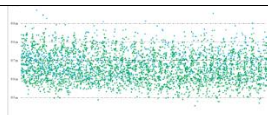
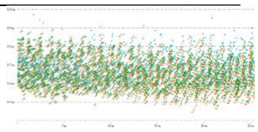
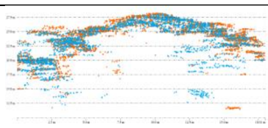
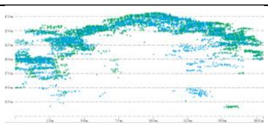
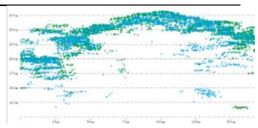
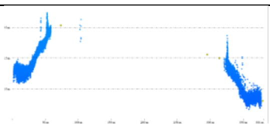
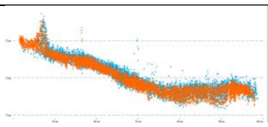
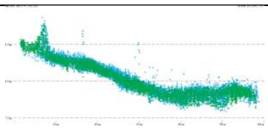
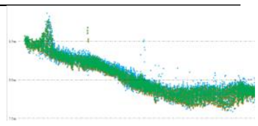
Source: Data Processed

RESULT AND DISCUSSION

Comparison of the point-to-point and point-to-plane adjustment results using the RMSE, fitness and correspondence parameters, shown in Table 3.
Based on the table above, it is known that the results of point-to-plane processing can improve the root mean square error value from point to point with a very significant increase from 8.71 centimeters to 1.53 centimeters. The transformation value from the point-to-plane registration method is smaller than the point-to-point results, which are mainly in the translation value.

In general, the two methods do not show a significant difference in the results of the strip adjustment. It is proven that the registered data point-to-point method (illustrated in orange data) can be passed over to the reference data depicted in blue data. Likewise, with the results of the point-to-plane method, the registered data (illustrated in green data) can be superimposed on the reference data depicted in blue data. The two results. show no significant gap between the registered data and the reference data because, in the cross-section depicted, the two data in the two results overlap, with the gap difference being under 1 centimeter.

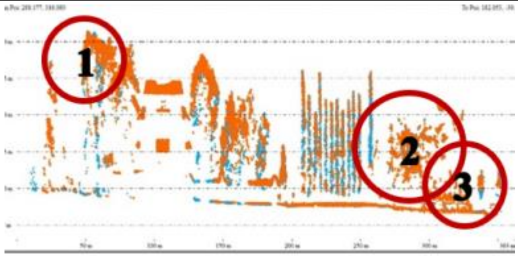
Table 4
Comparison of the Appearance of Objects

Object	Data	Point-to-Point ICP Result	Point-to-Plane ICP Result	Point-to-Point and Point-to-Plane Overlay
Roof				
Road				
Vegetation				
Ground				

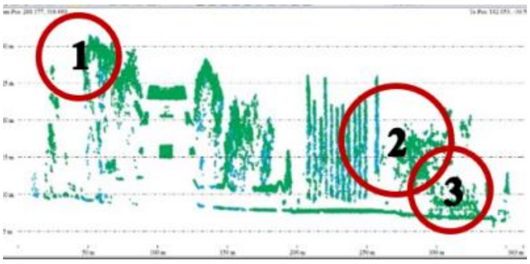
But in detail (Table 4), it can be seen that the data processed by the point-to-point method is farther away from the blue data, which is the reference data. In contrast, the appearance of the data processed by the ICP point-to-plane method has better results than the data processed by the point-to-point method because the data processed by the point-to-point method the ICP plane is closer to the blue data which is the reference data for strip adjustment processing. Based on its visual appearance, the results of the point-to-plane procedure are more suitable for each type of land cover, be it roofs, vegetation, roads, or ground.

However, if observed further, there are several locations where the data was successfully patched, showing that the point-to-plane method produces more fit registration results than the point-to-point method because the gaps between the resulting data are more petite. This can be observed in Figure 7.

Based on Figure 7, the locations circled in red indicate locations where there is a visible difference in fitness between the reference data and the registered data from the two registration methods used. At each location, it can be seen in each row and column in the table that the results from the point-to-plane method appear fitter in combining the data, which must be registered with reference data. These three locations also reinforce the finding that the point-to-plane method is better than the point-to-point method in registering overlapping points. When viewed in terms of the type of land cover, the three locations are vegetated areas.



(a)



(b)

Figure 7. Locations that Indicate Differences (a) From Point-To-Point (b) Form Point-To-Plane

The Cloud-to-Cloud (C2C) analysis (Table 5) demonstrates a clear difference in registration quality across the visual inspection of object classes. There are the comparison of Iterative Closest Point (ICP) result to ground truth. Well-defined, geometrically simple planar surfaces like building walls and the ground plane were registered with exceptionally high, sub-centimeter accuracy. Conversely, the road surface shows a significantly lower degree of correspondence, suggesting potential challenges in registering surfaces with different textural or reflective properties, or indicating a possible systemic vertical offset for that specific dataset.

A visual inspection reveals a high degree of spatial correspondence for the roof and ground classes.The vertical planar surfaces of the roof exhibit the highest level of agreement. The point cloud is overwhelmingly dominated by dark blue colors, corresponding to the lowest values on the color scale. The scale indicates that the maximum deviation for this class is approximately 0.0035 meters (3.5 mm). The slightly larger, yet still minimal, deviations (green to yellow) are concentrated at the geometric edges and corners of the structures. This is an expected outcome, as these areas are more susceptible to minor misalignments and differences in point density. The ground plane demonstrates a similarly high level of accuracy. The surface is predominantly green and blue, with its color scale maxing out at approximately 0.0050 meters (5.0 mm). This indicates a sub-centimeter level of agreement across the majority of the surface. The consistency of the color across the planar area suggests a robust and accurate registration for this object class.

In stark contrast to the building and ground, the road surface exhibits significantly larger C2C absolute distances. The color scale for the Road class spans a much larger range, with a maximum deviation of approximately 0.3872 meters (38.7 cm). This is nearly two orders of magnitude greater than the deviations observed on the building and ground surfaces. Visually, while there are areas of green (representing deviations around 2-5 cm), there are prominent patches of yellow and orange, indicating substantial

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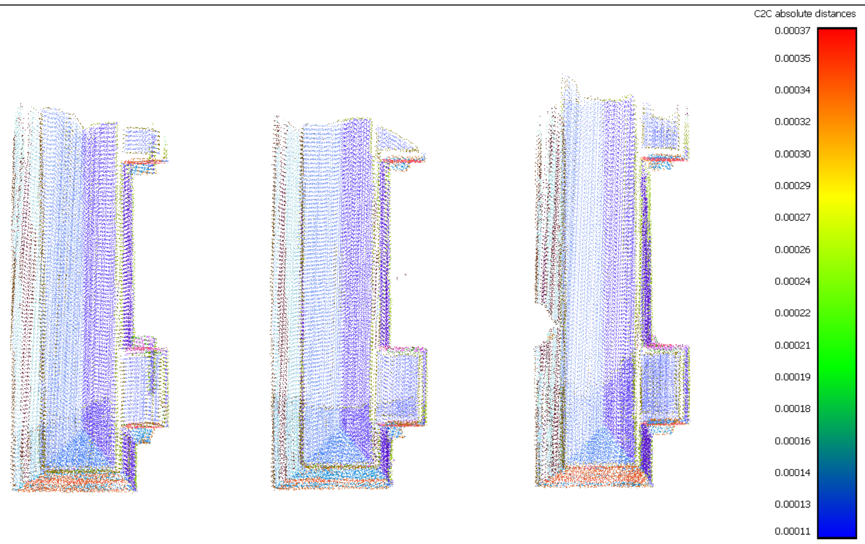
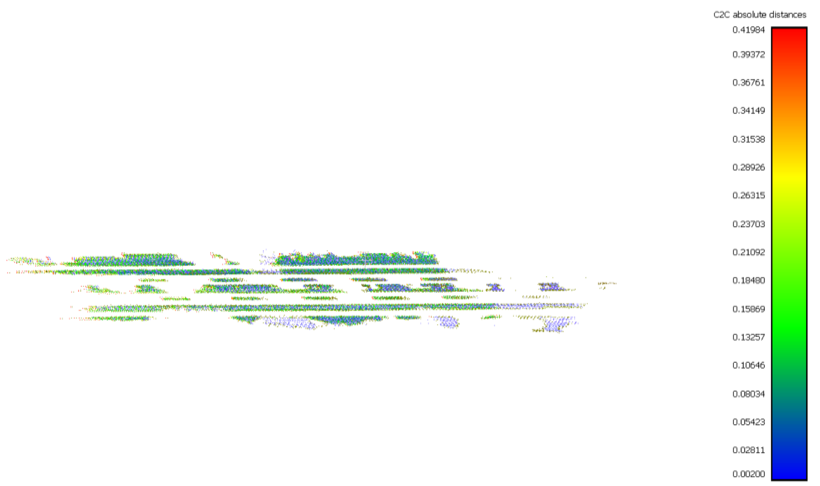
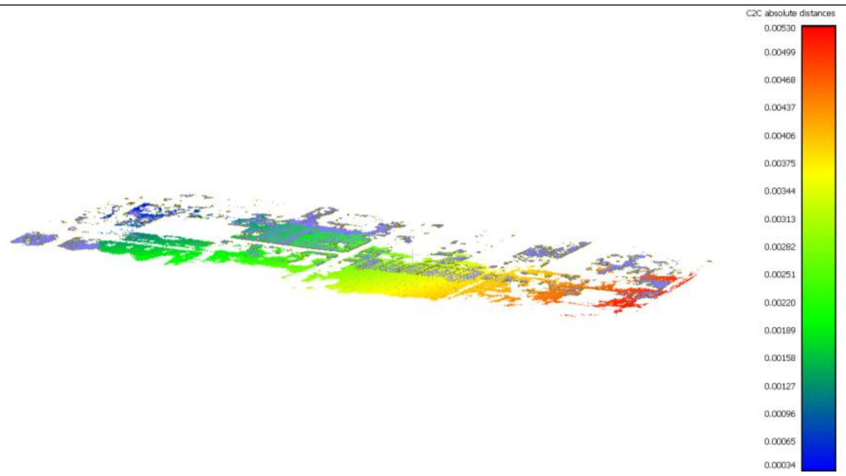
discrepancies. These larger deviations appear to be distributed across the surface, including on features that may represent road markings.

Table 5
Comparison of the Appearance of Objects

Object	Point-to-Plane compared to Ground Truth
Roof	
Road	
Ground	

Source: Data Processed

CONCLUSIONS

The point-to-plane registration method in the Iterative Closest Point (ICP) algorithm that is applied to LiDAR point cloud data on the earth's surface can improve the accuracy of the strip adjustment results. In addition, the strip results with the point-to-plane registration method proved to be fitter in combining overlapping point cloud data in the two scenes compared to the point-to-point registration method. This proves that the gap between overlapping points in the point-to-plane registration results is smaller than in the point-to-point registration results. The point-to-plane registration method in the Iterative Closest Point (ICP) algorithm applied to LiDAR point cloud data on the earth's surface can reliably be used for each type of land cover. This is evidenced by the improvement in the root mean square error value when processing every land cover compared to the point-to point method. In addition, based on its visual appearance, the results of the point-to-plane procedure are more suitable for each type of land cover. Based on this research, this method produces the best results when registering objects on the ground surface and roof.

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