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Common-Plane-Based Registration for 3D Point Clouds †

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Abstract

The importance of digital twins has been increasing, and high-precision registration is required for their construction. However, existing methods face the challenge of reduced registration accuracy due to the influence of non-overlapping regions between 3D point clouds. We developed a registration method that extracts and utilizes only common planar regions. In this method, common planes are automatically extracted using fast point feature histograms and a mutual nearest neighbor condition, and registration is performed using only these planes. Experimental results confirm the effectiveness of the proposed method under conditions that include non-overlapping regions.

Keywords: digital twin; registration; 3D point clouds; fast point feature histograms

1. Introduction

The utilization of three-dimensional spatial information has been rapidly advancing worldwide toward the realization of digital twins, which reproduce real-world environments in digital space. The digital twin market continues to expand and is projected to reach approximately USD 150 billion by 2030 [1]. Large-scale investments are being made globally, and long-term growth to approximately USD 300 billion is expected [2].

A national-scale digital twin project, Virtual Singapore [3], has been utilized for applications such as urban planning, disaster prevention, and environmental simulations. In Europe, the European Commission is promoting a global digital twin initiative known as Destination Earth [4], which is expected to be applied to climate change and natural disaster prediction. In Japan, the Ministry of Land, Infrastructure, Transport and Tourism is leading Project PLATEAU, which aims to develop and publish 3D city models for realizing digital twins across the country. Onishi et al. conducted evacuation simulations for both indoor and outdoor environments and examined urban safety planning by constructing a 3D spatial information infrastructure for TAKANAWA GATEWAY CITY in Minato City, Tokyo [5].

One of the fundamental technologies supporting these digital twins is 3D point cloud data. Point cloud data can represent the shapes of objects and terrains with high accuracy and is widely used in various fields such as urban planning, manufacturing, and healthcare. Methods for acquiring such data include using laser scanners to irradiate objects from the ground or air, and generating 3D models from multiple images using structure from motion and multi-view stereo. Light detection and ranging (LiDAR) has also been integrated into smartphones and tablets, enabling low-cost and easy acquisition of 3D point cloud data.

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However, in many cases, a single measurement is insufficient to fully capture a target object. Therefore, it is necessary to integrate data acquired from different paths into a unified spatial representation. This process is known as registration and is an essential preprocessing step in point cloud analysis. When the measurement range is large and cannot be fully covered in a single observation, or when observations are conducted at multiple locations to capture terrain changes, registration is required to correct misalignments caused by differences in observation conditions and to align the data to a common coordinate system [6].

3D point cloud data acquired in real environments often vary significantly in density, noise, and coordinate systems depending on sensors and observation conditions when used in digital twins and large-scale 3D urban models. Therefore, accurately integrating such data is key to improving overall quality. Accordingly, registration in 3D point cloud processing is a critical step that requires high-precision methods capable of handling diverse conditions.

2. Related Works

2.1. Geometry-Based Methods

Among the most fundamental approaches to 3D point cloud registration are geometry-based methods. Representative examples include iterative closest point (ICP) [7], which is based on point-to-point distance minimization, and its extension, generalized ICP (G-ICP) [8], both of which are widely used. ICP is used to estimate rigid transformations by minimizing the distances between corresponding points, enabling simple and highly accurate registration. In contrast, G-ICP is used to treat point clouds as probabilistic distributions and achieves stable registration by considering local structures through covariance matrices. These methods are still widely used today and serve as fundamental techniques in point cloud processing.

2.2. Feature-Based Methods

In contrast to methods that rely solely on geometric information, approaches have also been proposed to describe the local structure of point clouds as features and perform correspondence matching based on them. Representative features include the signature of histograms of orientations [9] and fast point feature histograms (FPFHs) [10]. These features represent geometric relationships within the neighborhood of a point as histograms and estimate correspondences between point clouds based on the similarity of these features. Feature-based methods have the advantage of being less dependent on the initial alignment and capable of establishing correspondences over a wide search range.

2.3. Learning-Based Method

Registration methods based on deep learning have also been actively studied. With the emergence of models that directly process point clouds as input, approaches have been proposed that jointly perform feature extraction and registration. PointNet + Lucas–Kanade [11] and the Robust Point Matching Network [12] are representative methods that achieve high-accuracy registration by simultaneously learning correspondence estimation and transformation estimation. Compared to conventional methods, these approaches offer higher robustness and can handle more complex environments.

2.4. Research Positioning and Challenges

The geometry-based, feature-based, and learning-based methods described above are all effective approaches for point cloud registration; however, they generally assume that sufficient overlapping regions exist between point clouds. In real-world environments,

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due to differences in sensor viewpoints and the effects of occlusion, point clouds often contain large non-overlapping regions. In such cases, the presence of numerous incorrect correspondences leads to a degradation in registration accuracy.

Geometry-based methods such as ICP and G-ICP are particularly sensitive to such errors, as incorrect correspondences directly affect transformation estimation, making them prone to convergence to local optima or incorrect alignments. Similarly, feature-based and learning-based methods may also produce incorrect correspondences when non-overlapping regions are dominant, due to errors in similarity evaluation or feature learning. Therefore, reducing the influence of non-overlapping regions and extracting stable correspondences based on overlapping regions remains a critical challenge.

This issue can be addressed using a registration method that does not rely on the entire point cloud but instead automatically extracts only common planar regions for registration. By doing so, the influence of non-overlapping regions is suppressed, enabling accurate and stable registration.

3. Method

The developed registration method in this study excludes planar regions in non-overlapping areas and utilizes only overlapping planar structures. First, planes are extracted from each point cloud, and planar clusters are generated. Next, the similarity between clusters is evaluated based on their FPFH features, and corresponding planes are automatically identified as common planes. Finally, registration is performed using these extracted planes. The detailed processing procedure of the proposed method is described as follows.

The input contains two 3D point cloud datasets, and the output is a single 3D point cloud aligned in a common coordinate system. The method targets point clouds acquired in real environments and consists of five main steps: downsampling, plane detection, local feature extraction, common plane extraction, and registration. The overall processing flow of the proposed method is shown in Figure 1.

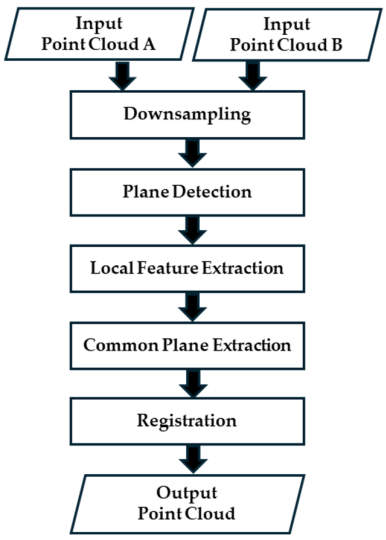


Figure 1. Flow of the proposed method.

3.1. Downsampling

The downsampling process is performed to reduce the number of points in a point cloud and to decrease the computational cost of subsequent processing. Since point clouds are typically acquired at high density, all points lead to increased computation time and reduced processing efficiency. Therefore, by appropriately reducing the number of points,

efficient registration can be achieved, preserving the essential geometric structure. Voxel grid downsampling is applied. The 3D space is divided into voxels of a fixed size, and the points within each voxel are replaced by their centroid, thereby reducing the total number of points. Figure 2 shows the point clouds before and after the process.

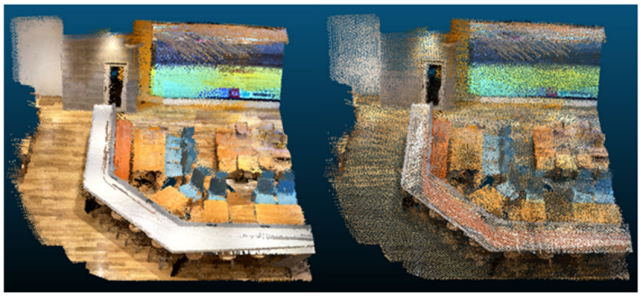


Figure 2. Images before (**left**) and after (**right**) downsampling.

3.2. Plane Detection

The plane detection process aims to extract planar regions from point clouds and generate candidates for common planes. Since point clouds acquired in real environments often contain many planar structures such as walls, floors, and desks, extracting these in advance is expected to enable more stable registration.

The proposed method combines plane detection using Random Sample Consensus (RANSAC) with clustering using Density-Based Spatial Clustering of Applications with Noise (DBSCAN). First, a plane model is estimated using RANSAC, allowing the extraction of point sets that serve as plane candidates while suppressing the influence of noise. Next, clustering based on spatial distribution is performed using DBSCAN. Since DBSCAN does not require the number of clusters to be specified in advance and can generate clusters based on point density, it enables segmentation of regions on the same plane while removing low-density points as noise. Figure 3 shows the point clouds before and after processing. The planes excluded by the plane detection process are highlighted with red boxes. As shown in Figure 3, small planar structures such as chairs and desks are removed, while large planar structures such as floors and walls are retained.

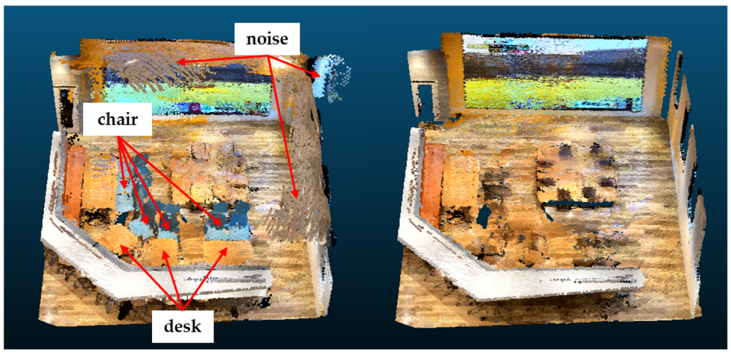


Figure 3. Images before (**left**) and after (**right**) plane detection.

3.3. Local Feature Extraction

The local feature extraction process computes FPFH, a local feature descriptor, for each plane obtained through the plane detection process. FPFH is a 33-dimensional feature that represents local geometric structures by describing the relationships between a point p and its neighboring points based on angular features α, ϕ, and θ. These angles are defined based on the relationships between points and their normal vectors. Since FPFH is

low-dimensional and computationally efficient, it is computed for each plane and used for similarity evaluation in the common plane extraction process.

3.4. Common Plane Extraction

After the local feature extraction process, correspondences between planes are established based on their similarity. The similarity is evaluated using FPFH for all possible pairs of planes obtained from the two point clouds. Plane pairs with high similarity are selected as correspondence candidates, and only those satisfying the mutual nearest neighbor condition are automatically extracted as common planes. This approach eliminates incorrect correspondences that exhibit high similarity in only one direction, enabling the selection of consistent and reliable plane correspondences.

3.5. Registration

As the final step, the corresponding planes are extracted from each point cloud, and two point clouds composed of the common planes are generated. G-ICP is then applied to these two point clouds, and registration is performed by iteratively minimizing the error between corresponding points.

4. Performance Evaluation

The experimental evaluation consists of three parts: verification of common plane extraction accuracy, comparison of registration accuracy with and without the common plane extraction process, and evaluation of registration accuracy at different overlap ratios under translation and rotation conditions. The experimental data contain four real-world point clouds acquired using an iPad Pro (Apple Inc., Cupertino, CA, USA) equipped with LiDAR in a study space, free space, corridor, and classroom at Kyoto Tachibana University in Japan. The datasets are shown in Figure 4.

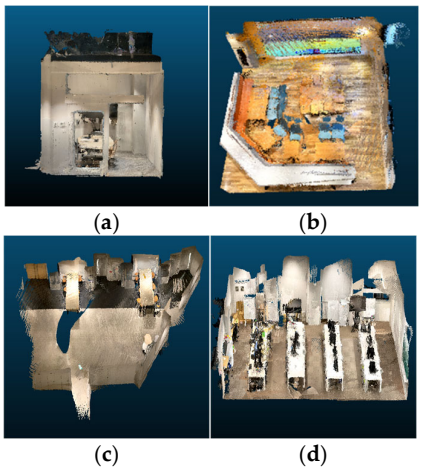


Figure 4. 3D point cloud datasets used in the experiments: (**a**) Environment 1, (**b**) Environment 2, (**c**) Environment 3, and (**d**) Environment 4.

4.1. Evaluation of Common Plane Extraction Accuracy

An experiment was conducted to evaluate the accuracy of common plane extraction, which is a key feature of the proposed method. The plane correspondences obtained using FPFH and the mutual nearest neighbor condition were evaluated in terms of precision and recall. Ground truth common planes were manually defined for each environment through visual inspection, and true positives (TPs), false positives (FPs), and false negatives (FNs) were computed by comparing them with the automatically extracted results. The experimental results are shown in Table 1.

Table 1. Experimental results.

Parameter	Environment 1	Environment 2	Environment 3	Environment 4
GT	5	10	12	11
Detected pairs	5	9	11	8
TP	5	9	9	4
FP	0	0	2	4
FN	0	1	3	7
Precision	1.000	1.000	0.818	0.500
Recall	1.000	0.900	0.750	0.364

In Environment 1, no false detections or missed detections occurred, resulting in high precision and recall. In Environment 2, while false detections were suppressed, missed detections occurred due to partially observed planes. In Environment 3, both missed detections and false detections were observed due to noise and incorrect correspondences with non-overlapping planes. In Environment 4, the presence of many desk planes with similar shapes made it difficult for FPFH to distinguish between them, leading to an increase in both missed detections and false detections, and consequently, a decrease in accuracy.

These results indicate that the proposed method can accurately extract common planes in environments with clear structural features. However, in environments with many similar shapes, correspondence based solely on FPFH similarity has limitations. To address this issue, we plan to improve the processing pipeline, for example, by introducing a preprocessing step to remove identical objects before the plane detection stage.

4.2. Comparison of Registration Accuracy with and Without Common Plane Extraction

In this experiment, the registration accuracy of using all planes (all planes) and using only common planes (common planes) is compared in terms of the root mean square error (RMSE). Figure 5 shows the temporal changes in RMSE for each environment.

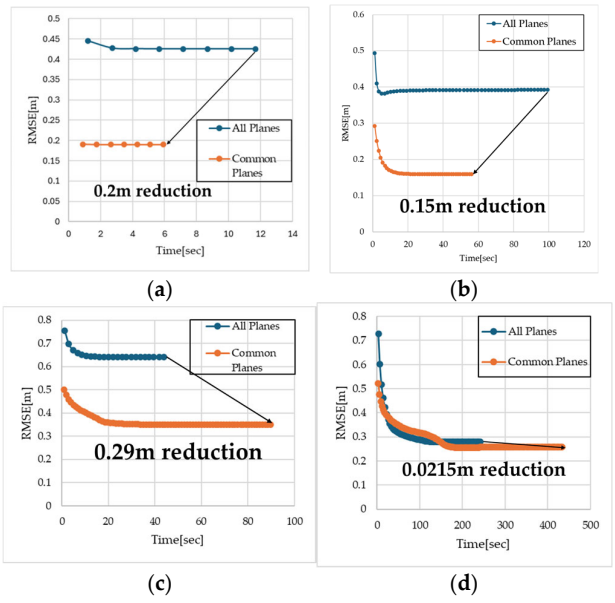


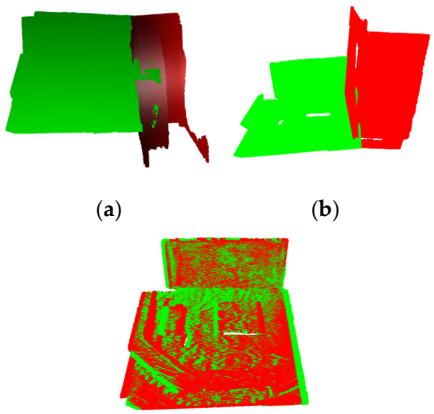
Figure 5. Comparison of RMSE over time between registration using all planes and only common planes: (**a**) Environment 1, (**b**) Environment 2, (**c**) Environment 3, and (**d**) Environment 4.

The developed method achieves lower RMSE values across all environments, demonstrating improved registration accuracy. In Environments 1 and 2, the use of common

planes enables rapid and stable convergence of RMSE. In Environment 3, even under conditions where the accuracy of common plane extraction is insufficient, the method reduces RMSE by approximately 0.29 m compared to the conventional method. This indicates that the proposed method can suppress the influence of non-overlapping regions and contribute to stable registration even when the accuracy of common plane extraction is not sufficiently high. However, in environments such as Environment 4, where many similar planes exist and the accuracy of common plane extraction is significantly low, the performance is comparable to that of the conventional method.

4.3. Evaluation of Registration Accuracy at Different Overlap Ratios Under Translation and Rotation Conditions

In real-world environments, it is common for the spatial positions and orientations of point clouds to differ due to variations in acquisition time and measurement devices. Therefore, we evaluated registration performance under such conditions using Environment 2, where the accuracy of common plane extraction was relatively high. In addition, to examine the effect of overlap, evaluations were performed at different overlap ratios. One of the point clouds was transformed by applying translation and rotation along the X and Y axes. The overlapping region was then controlled by dividing the common area based on the centroid of the floor, which contains the largest number of points. By adjusting the size of the common region, five overlap ratios (90, 80, 70, 60, and 50%) were generated to form pairs of point clouds. The registration result for the 90% overlap case is shown in Figure 6, and the results for all overlap ratios are summarized in Table 2.



(**a**) (**b**)

(**c**)

Figure 6. Registration results at an overlap ratio of 90%: (**a**) all points, (**b**) all planes, and (**c**) proposed method.

Table 2. Registration results for each overlap ratio.

Overlap Ratio (%)	All Point Cloud (m)	All Planes (m)	Proposed Method (m)
90%	0.442897	0.419195	0.046211
80%	0.437204	0.411932	0.145192
70%	0.441423	0.477353	0.334176
60%	0.443589	0.441123	0.422600
50%	0.443599	0.414829	0.483920

As shown in Figure 6, stable registration was not achieved under any condition when using all points or all planes. In contrast, the proposed method achieved stable registration and reduced RMSE in the overlap ratio range of 90 to 70%. Even under translation and rotation conditions, the use of only common planes suppresses the influence of non-overlapping regions. However, when the overlap ratio was 60% or lower, cases

of registration failure were observed even with the proposed method. This is considered to be due to the nature of G-ICP, which establishes correspondences between spatially closest points, leading to incorrect correspondences between structures such as walls and floors that are not originally corresponding but become spatially close due to translation and rotation. These results indicate that the developed method functions effectively when the overlap ratio is 70% or higher, whereas under low-overlap conditions, errors in plane correspondence become a major factor degrading performance.

5. Conclusions

We developed a registration method for 3D point cloud data that focuses on planar structures rather than the entire point cloud and utilizes only common planes. Local features were computed for each plane using FPFH, and effective correspondences were selected by extracting common planes based on similarity evaluation under a mutual nearest neighbor condition. A key feature of the proposed method is its ability to suppress the influence of non-overlapping regions. To validate the effectiveness of the method, experiments were conducted in four different real-world environments. The results showed that in environments with clear planar structures, common planes can be extracted with high accuracy, leading to a reduction in RMSE compared to conventional methods. In addition, more stable registration was achieved than with existing methods even under translation and rotation conditions. These results indicate that the developed method is useful as a fundamental technique for achieving stable registration in various applications utilizing 3D point cloud data, such as autonomous driving maps, digital twins, and disaster situation assessment. A limitation exists in environments containing many planes with similar shapes, where registration accuracy decreases. Therefore, it is necessary to improve the plane detection pipeline by introducing a same-object removal process and evaluating registration accuracy under varying overlap ratios in other environments.

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