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Ground-based Multi-platform Point Clouds Registration

Yuan Gao* and Mingchu Li

School of Software Technology, Dalian University of Technology, Dalian 116620, China;

* Correspondence: 937018401@qq.com; ssdut@dlut.edu.cn

Abstract: Laser scanning system provides an efficient solution to rapidly acquire 3D information of large-scale scenes. Point clouds collected by laser scanning systems contain numerous objects with significant disparities in size, complicated and incomplete structures, holes, varied point densities, and huge data volumes, raising great challenges for automated point clouds registration, segmentation, and object detection. The dissertation presents a hierarchical merging based multi-platform point clouds registration algorithm to align MLS point clouds and unordered TLS point clouds from various scenes and validates its performance on nine challenging datasets. The algorithm improves the efficiency and accuracy of point cloud registration and enhances the registration ability of the algorithm for low-overlap and high-symmetry point clouds.

Key words: Point clouds, automatic registration, Urban scene mapping

1. Introduction

When the mobile laser scanning system (MLS) acquires the three-dimensional data of the ground objects around the road, the data of the three-dimensional target in the scene is incomplete due to the mutual occlusion between the targets, which seriously affects the accuracy of target recognition and model reconstruction. In practical applications, MLS is used to collect large-scale cities or high-speed scene point clouds, and then TLS is used to supplement the key areas and data holes to compensate for the lack of data coverage and scene representation of a single laser scanning system. There are spatial benchmarks, observation angles, and data quality differences between ground-based multi-platform laser point clouds, which poses a huge challenge to ground-based multi-platform laser point cloud automated registration.

Aiming at the low efficiency of existing ground-based multi-platform point cloud registration algorithm, difficulty in solving low overlap registration, lack of MLS and TLS point cloud registration theory research, this paper proposes a fast and robust ground-based multi-platform laser point. Ground-based Multi-platform Point Clouds Hierarchical Registration (GMPCHR), which realizes multi-view TLS point cloud registration under unified theoretical framework and multi-view TLS and MLS point cloud registration, improving point cloud matching. The quasi-efficiency, accuracy, and scope of application enhance the registration ability of the algorithm for low-overlap and high-symmetry point clouds.

2. Related work

When MLS obtains the 3D data of the ground objects around the road, the data of the 3D target in the scene is incomplete due to mutual occlusion between the targets, which seriously affects the accuracy



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of target recognition and model reconstruction, and limits the actual efficiency of the laser scanning system. In practical applications, MLS is used to collect large-scale cities or high-speed scene point clouds, and then TLS is used to compensate key areas and data holes to make up for the lack of data coverage and scene expression of a single laser scanning system. There are spatial benchmarks, observational perspectives, and data quality differences between the MLS point cloud and the TLS point cloud, which poses a challenge for automatic registration of MLS and TLS point clouds.

In order to reduce the computational complexity and improve the efficiency of point cloud registration, scholars propose a multi-view cloud registration strategy based on shape growth ([1], [2]). The multi-view cloud registration method based on shape growth first selects the point cloud with the largest surface area or the maximum number of points as the seed point cloud, then pairs the seed point cloud and other point clouds, and finally merges with the seed point cloud. There is a point cloud with enough pairs of features of the same name. Iterate through the above process until all point clouds are merged. Compared with the algorithm based on minimum spanning tree and global energy optimization, the algorithm has lower computational complexity and higher computational efficiency. However, it has higher requirements on point cloud overlap and cannot solve low-overlap point cloud registration.

Yu et al proposed a multi-scale ICP method to achieve non-rigid registration of overlapping MLS point clouds [3]. The algorithm first detects the features of each feature in the point cloud, and divides them into five levels according to the size of the feature. Then, according to the order of size from large to small, the features of each layer are used as the input of the ICP algorithm to carry out the point cloud registration; finally, the rigid transformation combination of multiple cubic spline control points is used to express the non-rigid transformation model. Yang et al firstly use FPFH and semantic feature points as feature descriptors to perform exhaustive pairwise registration, and then calculate the number of the same name features between point clouds as weights to construct an undirected weighted graph. Finally, the method implements the conversion of any point cloud to the reference point cloud by calculating the minimum spanning tree of the graph [4]. Zai et al fused the feature similarity and geometric consistency to construct the global energy equation, and transformed the problem of point cloud registration into the problem of energy optimization; then used the game theory method to optimize the solution to obtain the global optimal feature set of the same name [5]. This method improves the accuracy and recall rate of feature recognition of the same name, but the computational complexity is high and it is difficult to apply to large-scale point cloud registration. Yan et al first segmented the on-board laser point cloud according to the trajectory and removed its ground point cloud; then used the point cloud three-dimensional bounding box to find the overlapping point cloud and used the improved ICP method for registration. Overlapping point clouds; finally, using the registration parameters to reverse the positioning and attitude error of the on-board laser scanning system [6]. When there is a large deviation between overlapping MLS point clouds, the ICP algorithm will converge to the local extremum, resulting in registration failure.

3. Method

3.1. Data preprocessing

In this paper, the point density in the three-dimensional neighborhood is used to remove the abnormal points in the point cloud, and the remaining point clouds are subjected to regular down-sampling. Then, along the direction of the vehicle's trajectory, the point cloud is divided into a series of local point clouds in a XY plane according to a certain width, length and overlap.

3.2. Point cloud multi-level feature calculation

This paper calculates the local feature descriptors of key points in the laser point cloud and the point cloud global feature descriptors of the point cloud block. This paper develops a point cloud overall aggregation descriptor, which realizes the accurate characterization of the overall characteristics of the laser point cloud by encoding the BSC descriptors of all key points in the point cloud. The algorithm

first randomly selects the BSC descriptors of N key points from all laser point clouds, and uses the K-means algorithm to cluster them into K categories, and uses the K-type center as a visual word to obtain a visual dictionary. Then, calculate the laser separately. The sum of the BSC descriptors of all key points in the point cloud to the residuals of their corresponding visual words; finally, the residuals of all the visual words are concatenated and normalized to be the global aggregate descriptor (GAD) of the point cloud.

3.3. Point cloud near-neighbour (overlapping) structure diagram fast construction

The relative position between the ground-based multi-platform laser point cloud registration midpoint clouds is unknown, increasing the complexity of point cloud registration. In order to estimate the relative position between the point clouds, most existing algorithms first perform an exhaustive pairwise registration of the point clouds in the scene, and then filter the point clouds with large overlap by pre-defined registration indicators. Such methods are computationally time consuming and difficult to apply to ground-based multi-platform laser point cloud registration for large scenes. This paper develops an adjacent (overlapping) point cloud efficient indexing method based on point cloud overall aggregation descriptor similarity, which realizes the rapid construction of point cloud neighbor (overlap) structure relationship diagram, which reduces the complexity of ground-based multi-platform laser point cloud registration algorithm.

The two-point cloud with large overlap contains more BSC descriptors with the same name, so its corresponding point cloud overall aggregation descriptor GAD has greater similarity. Specifically, the similar components and dissimilar components in the GAD descriptors of adjacent two-point clouds are derived from their overlapping and non-overlapping regions, respectively. Based on the above considerations, this paper first calculates the Manhattan distance of K corresponding components between GAD features, and reorders them according to the distance from small to large; then calculates the similarity between features and calculates the overlap between point clouds.

In order to verify the relationship between GAD feature similarity and its corresponding point cloud overlap, this paper uses linear regression analysis to calculate the correlation between them. For any point cloud, first calculate the overlap degree between the point cloud and other point clouds and the corresponding GAD feature similarity; then use the degree of overlap as the abscissa, and the normalized similarity as the ordinate to form the data point; finally, the method of squares fits the regression equation and calculates the deterministic coefficient R^2 of the equation.

3.4. The best registration point cloud pair calculation considering the maximum overlap degree

The two point clouds with large overlap have more similar features. We use the overall aggregation of the point cloud to describe the sub-similarity to indirectly reflect the overlap between the point clouds, and preferentially match the point cloud with the most similarity of the point cloud GAD. We use a two-two-point cloud registration algorithm that combines BSC to describe sub-similarity, geometric consistency and visual compatibility, and register the two sets of point clouds with the largest aggregate similarity in the overall aggregation descriptor, including the BSC descriptor matching of the same name. There are four main steps to improve geometric consistency, such as error matching culling, space conversion parameter calculation, and visual compatibility testing. Finally, we merge the source point cloud and the target point cloud that satisfy the visual compatibility into a new point cloud and calculate its BSC descriptor sub-set. We use the BSC to describe the sub-sets and incremental merges to obtain the BSC descriptor sub-sets of the new point cloud, thus implementing point cloud fusion.

4. Experimental results and analysis

4.1. Multi-view TLS point cloud registration results

Figure 1 shows the overall and detailed results of the multi-view TLS point cloud registration at 32 stations of Wuhan Longquanshan Park. Figure 1a and b are the details of one of the building

registrations and the station location of the scanning station, point clouds of different scanning stations are represented by different colors.

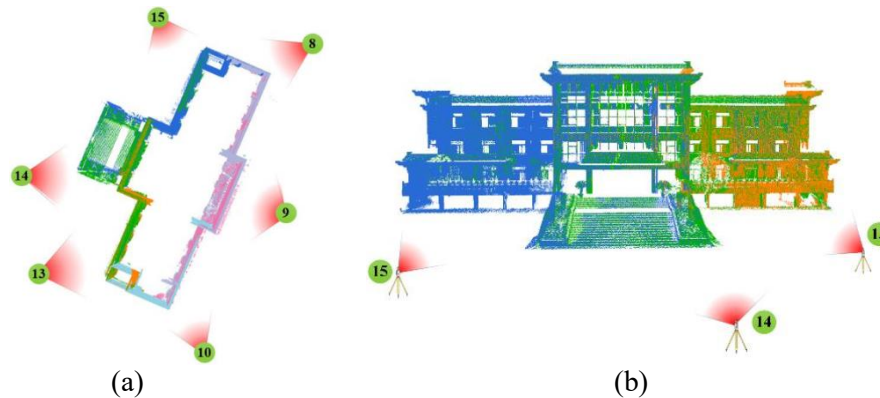


Figure 1. Overall and details of multi-view TLS point cloud registration at 32 stations of Wuhan Longquanshan Park.

4.2. Multi-view TLS and MLS point cloud registration results

Figure 2 shows the overall and detailed results of the algorithm's MLS point cloud and 5-station multi-view TLS point cloud registration at the School of Geographical Sciences. Figure 2 shows the results of MLS point cloud and multi-view TLS point cloud registration, as well as the position of the multi-view TLS point cloud station. The MLS point cloud is shown in gray, and the TLS point clouds of different scanning stations are represented by different colors.

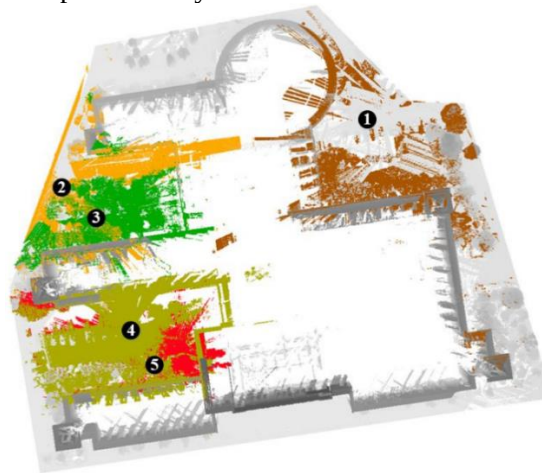


Figure 2. Results of MLS point cloud and multi-view TLS point cloud registration

4.3. Registration Accuracy Quantitative Evaluation and Analysis

In this paper, the minimum, maximum, mean and root-mean-square errors of the rotation angle error and translation error, as well as the accuracy of registration, are used to quantitatively evaluate the performance of the proposed method. In order to obtain the true value of the point cloud registration, this paper first uses the manually labeled pair of points with the same name to perform rough point cloud registration, and then uses the multi-view ICP algorithm for fine registration. The experimental results show that the ground-based multi-platform laser point cloud registration method achieves excellent performance in multi-view point cloud registration, multi-view TLS, and MLS point cloud

registration in different scenes. The average rotation angle error is less than 0.1 degree. The translation error is less than 0.1 meters, which can meet the three-dimensional target extraction and three-dimensional reconstruction accuracy requirements.

4.4. Quantitative evaluation and analysis of time efficiency

This section quantitatively evaluates the complexity of the registration algorithm, the time spent for each key step, and the total elapsed time. Experimental results show that the multi-platform laser point cloud registration method proposed in this paper achieves high computational efficiency in multi-view TLS point cloud registration, multi-view TLS, and MLS point cloud registration in different scenarios. In particular, it is worth noting that the number of two-by-two registrations in this paper is obviously less than the number of exhaustive registrations. It takes only half an hour to automate the registration of TLS points in 32 stations of Wuhan Longquanshan Park, significantly improving the computational efficiency.

4.5. Experimental comparison and discussion

In order to further analyze the performance of the GMPCR algorithm, the paper compares the current multi-view TLS point cloud registration algorithms from four aspects including accuracy of registration, rotation angle error, translation error, and algorithm time-consuming. As shown in Table 1. At the same time, in order to verify the impact of local feature descriptors and multi-view matching strategies on the performance of the registration algorithm, this paper also analyzes the performance of variants GMPCR* and GMPCR# of the GMPCR algorithm. The GMPCR# and GMPCR* use the multi-view TLS point cloud matching strategy based on the minimum spanning tree and the multi-view TLS point cloud matching strategy based on shape growth instead of the hierarchical registration strategy in this paper, the other steps are consistent with the GMPCR algorithm.

Table 1. Algorithm performance comparison

Data set		SRR (%)	Rotation angle error		Translation error $\boldsymbol{e}_{r,i}^t$		operation
			$\boldsymbol{e}_{r,i}^r$ (mdeg)		(mm)		hours
			Ave	RMSE	Ave	RMSE	(min)
Wuhan	Weber et al., 2015	100.0	49.1	12.4	43.3	7.2	361.6
Longquan	GMPCR*	100.0	48.6	9.8	42.9	8.1	177.8
shan Park	Guo et al., 2014	100.0	44.5	13.7	37.2	9.4	186.2
	GMPCR#	100.0	44.7	13.6	36.8	9.8	94.6
	GMPCR	100.0	40.2	9.2	31.1	8.0	39.5

5. Conclusions

Aiming at the problems of the existing ground-based multi-platform point cloud registration algorithm, such as low efficiency, difficulty in resolving low overlap registration, lack of theoretical research on MLS and TLS point cloud registration, etc. This paper presents a fast, robust method for automatic registration of ground-based multi-platform LiDAR point clouds, which achieves a multi-vision TLS point cloud registration and multi-view TLS and MLS point cloud registration under a unified theoretical framework. The results of comprehensive comparison experiments show that the proposed method for multi-platform LiDAR point cloud registration improves the efficiency, accuracy, and scope of point cloud registration, and enhances the ability of the algorithm to register with low overlap and high symmetry point clouds. In the future work, the ground-based multi-platform LiDAR point cloud registration method will be further optimized and expanded, including: closed-loop automated detection and redistribution of registration errors based on closed-loop constraints; further improve the

theoretical system of multi-platform point cloud registration, and expand this method for multiplatform laser point cloud registration such as TLS, MLS and ALS.

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