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Research on Airborne Point Cloud Data Registration Using Urban Buildings as an Example

Yajun Fan, Yujun Shi, Chengjie Su, Kai Wang

School of Civil Engineering, Guangxi Polytechnic of Construction, Nanning 530007, Guangxi, China

Abstract: Airborne LiDAR (Light Detection and Ranging) is an evolving high-tech active remote sensing technology that has the capability to acquire large-area topographic data and can quickly generate DEM (Digital Elevation Model) products. Combined with image data, this technology can further enrich and extract spatial geographic information. However, practically, due to the limited operating range of airborne LiDAR and the large area of task, it would be necessary to perform registration and stitching process on point clouds of adjacent flight strips. By eliminating grow errors, the systematic errors in the data need to be effectively reduced. Thus, this paper conducts research on point cloud registration methods in urban building areas, aiming to improve the accuracy and processing efficiency of airborne LiDAR data. Meanwhile, an improved post-ICP (Iterative Closest Point) point cloud registration method was proposed in this study to determine the accurate registration and efficient stitching of point clouds, which capable to provide a potential technical support for applicants in related field.

Keywords: Airborne LiDAR; Point cloud registration; Point cloud data processing; Systematic error

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1. Introduction

Point cloud data is a collection of a large number of discrete points, where each point represents a series of measured positions on the surface of a target object. In three-dimensional space, each point has coordinates (X, Y, Z) to describe its position in the 3D space [1]. For urban building point cloud data acquired by airborne LiDAR systems, in addition to spatial coordinates, the point cloud data may also carry additional attributes such as reflection intensity and echo count. Such rich and diverse information makes point clouds an important medium for accurately expressing and analyzing the morphological and structural characteristics of urban buildings.

There are various ways to acquire point cloud data. Among them, airborne LiDAR, with its high precision, high efficiency and good adaptability to complex terrains, has gradually become one of the main means to obtain large area urban building point clouds [2]. The laser scanner mounted on airplanes or unmanned aerial vehicles emits laser pulses to the ground and receives reflected signals, which can quickly obtain the 3D coordinate information of the ground surface and its attachments. It can work effectively even in urban environments with many high rise buildings and compact layouts. Moreover, airborne LiDAR can complete large area data collection in a short time, which greatly improves work efficiency.

For urban buildings, the significance of point cloud data is far more than simple 3D reconstruction. By in depth mining of massive point cloud data, geometric parameters such as the height, area and volume of buildings can be extracted. Combined with texture mapping technology, the realistic reproduction of the appearance of buildings can also be realized. With the development of artificial intelligence technology, it has become possible to automatically identify different types of urban buildings from point cloud data using deep learning algorithms, which will help to further expand the application scope and value of point cloud data.

2. Material and methods

2.1. Data sources

The data used in this paper were acquired by the Rochester Institute of Technology (RIT) using the ALS60 airborne LiDAR system from Leica Geosystems, Switzerland [3]. The areas where data were collected include the Genesee River, downtown Rochester, and the RIT campus. The composition of the ALS60 LiDAR system is shown in **Figure 1**.

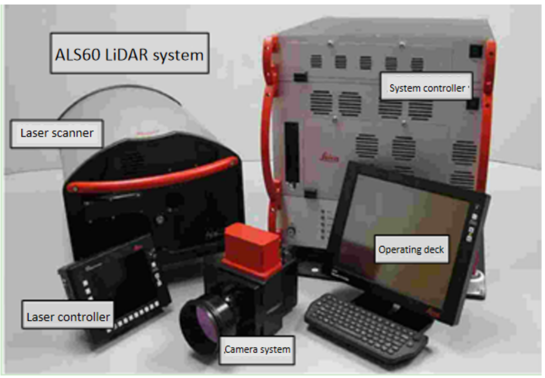

Figure 1. Leica ALS60 LiDAR Data Acquisition System

2.2. Study area

RIT requires specific flight missions to be carried out over Rochester, New York, involving 6 flight routes, 4 of which are within the RIT campus (see **Figure 2**). These routes include two north-south routes (RIT_1 and RIT_2) with approximately 30% overlapping area, as well as one east-west route and one route from southeast to northwest. The mission specifies a flight altitude of 1000 meters and a scan angle set at approximately 40° to ensure the acquisition of high-precision LiDAR data [4]. Since the scanning area is mainly within the campus, the terrain undulation is relatively gentle, and the surface features mainly include buildings, rivers, bridges, and trees. Such environmental characteristics provide relatively ideal conditions for data collection.

Figure 2. RIT Campus Route Planning Map and Data Collection Range

2.3. Point cloud filtering

Point cloud filtering is one of the key steps in airborne LiDAR point cloud data processing, and it is particularly important in the registration process of urban building point cloud data [5]. The main goal of point cloud filtering was to remove noise points and outliers from the original point cloud data while retaining valid building point cloud information, thereby improving the accuracy of subsequent registration.

In practical applications, common point cloud filtering methods include statistical based filtering methods and geometric feature-based filtering methods. Statistical-based methods identify and eliminate points with abnormally large distances from surrounding points by calculating the distance distribution between each point and its neighboring points. These methods were suitable for processing point cloud data with relatively uniform distribution. However, in scenarios with complex structures such as urban buildings, they may misjudge some valid points as noise points. To address this issue, an adaptive filtering strategy was introduced, which adjusts filtering parameters according to the local point cloud density to ensure effective noise removal while maximizing the retention of building details [6].

Geometric feature-based filtering methods focus more on the spatial distribution characteristics of point clouds. For example, normal vector consistency detection was found to effectively identify points that deviate significantly from the normal vector of the building surface. In urban environments, buildings usually have obvious planar or curved surface features. Therefore, the point cloud data that conform to the geometric characteristics of buildings can be screened by calculating the local normal vector of each point. In addition, filtering was performed in combination with the height information of buildings to remove low-altitude cluttered point clouds, such as non-building parts like vegetation and ground. This method was particularly effective when processing high rise buildings and has significantly improve the quality of point cloud data.

2.4. Airborne LiDAR strip mosaicking using the ICP algorithm

The ICP (Iterative Closest Point) algorithm played a crucial role in airborne LiDAR strip mosaicking. As an iterative closest point algorithm, it can effectively achieve precise alignment of data acquired from different scanning angles. Specifically, in urban building scenarios, airborne LiDAR systems, mounted on aircraft, collect three-dimensional information of the Earth's surface from the air. However, due to unavoidable factors such as attitude changes and positioning errors during flight, there is a misalignment phenomenon in the point cloud data between adjacent flight strips, which requires the used of the ICP algorithm for high-precision mosaicking processing [7].

For airborne LiDAR data, the core of the ICP algorithm lies in finding the optimal matching relationship between two sets of point clouds. This process first involves a point cloud preprocessing stage, which is to remove noise points and outliers to ensure the accuracy of subsequent calculations. In practical operations, voxel grid filtering or statistical filtering methods were usually used for initial noise reduction [8]. Then, key points with obvious features and uniform distribution were selected as matching benchmarks, such as landmark positions like building edges and corners. The selection of these key points directly affects the quality of the final registration result.

After determining the key points, the core iterative calculation stage was entered. The ICP algorithm disclosed the nearest target point in the other set of point clouds for each point to be registered, and then solved the rotation and translation transformation matrix between them based on the principle of the least squares method. This step was repeated until the convergence condition is met or the predetermined maximum number of iterations was reached. It is worth noting that in urban environments, due to the complex and diverse shapes of buildings, there may be multiple similar structures, which can easily lead to mismatches. Therefore, when selecting initial correspondences, efforts should be made to utilize global geometric features to avoid falling into the trap of local optimal solutions.

In practical applications, the ICP algorithm was not only limited to mosaicking between strips within a single flight mission but can also be used for integrating results from multiple flights [9]. As the continuous development and progress of UAV technology, more and more low-altitude, refined surveying and mapping work has been carried out. At this time, ensuring the consistency of cross-time data has become a new challenge. To this end, consideration can be given to constructing a unified coordinate framework, and effectively connecting point clouds of different time phases by introducing ground control points or other reference objects. At the same time, by considering the systematic deviations caused by weather conditions, sensor parameter drift should be done as these deviations may potentially interrupting the results obtained. Thus, corrections and compensations should be made to obtain more accurate and reliable three-dimensional models.

2.5. Experiment and analysis

In the experiment and analysis phase, the technical route for the registration research of airborne point cloud data, taking urban buildings as an example, involved a complex multi-step process. This process aimed to ensure the accurate fusion of LiDAR point cloud data of urban buildings acquired at different time periods, thereby providing a foundation for the construction of high-precision 3D models.

Point cloud preprocessing, as the first step of the technical route, was crucial for the accuracy of subsequent work [10]. Raw point cloud data often contains a large number of noise points and outliers, and the existence of these abnormal points potentially generating a negative impact on the registration results. Therefore, filtering algorithms were used to clean the raw data. Local statistical filtering is a commonly used method, which removed the points that do not meet the conditions as noise by setting the neighborhood range and threshold.

After preprocessing, the point cloud data enters the key link feature extraction. To achieve efficient and accurate registration, it was necessary to extract stable and unique features from the point cloud. Feature descriptors based on normal vectors are widely used in such tasks. The normal vector of each point and the statistical characteristics within its neighborhood were calculated to form a multi-dimensional feature vector. In addition, considering the structural characteristics of urban buildings, edge features and plane features were introduced as auxiliary information to enhance the reliability of feature matching [11].

After feature extraction, the coarse registration operation was carried out. The goal of this stage was to determine the approximate relative positional relationship between the two-point clouds in the global scope. Based on the above extracted feature information, the nearest neighbor search algorithm was used to find potential corresponding point pairs. However, due to the complexity and variability of actual scenes, direct use of nearest neighbor matching may introduce wrong matches [12]. For this reason, geometric constraints such as distance constraints and angle constraints were introduced in the screening part, and only point pairs that meet the logical relationship were retained as candidate matching pairs. Then, the least square method was used to solve the rotation matrix and translation vector, and the attitude transformation of the two point clouds is initially completed. Although the coarse registration result can make most of the point clouds overlap, there were still local deviations that need further optimization.

To address the problems left by coarse registration, the Iterative Closest Point (ICP) algorithm was introduced for fine registration [13]. The ICP algorithm was repeatedly iterated to find the closest point pairs and update the transformation parameters until the convergence criterion is met or the maximum number of iterations reached. In specific implementation, considering the large scale of urban building point cloud data, the direct application of the traditional ICP algorithm would be inefficient. Therefore, a hierarchical ICP strategy was adopted: first, perform rough registration on the sparsified point cloud with a larger voxel size, then gradually reduce the voxel size, and continue to optimize the point cloud at a finer level until a satisfactory result was obtained.

3. Results

Through a series of experimental verifications, the proposed airborne point cloud data registration method demonstrated excellent performance in urban building scenarios. After applying the registration process to point cloud data of various building types, the accuracy was significantly improved. The experimental results revealed that for modern urban building clusters characterized by numerous high-rise buildings and complex structures, using the improved ICP algorithm for point cloud data registration effectively reduced errors and enhanced data accuracy. For instance, during the collection and registration of point cloud data from multiple high-rise office buildings in a city’s central area, the original point cloud data was first filtered to remove noise and outliers. Subsequently, the feature-matching-based ICP algorithm was applied for registration. The final results showed that the registered point cloud data closely matched the actual buildings regarding contours and detailed features, with the error controlled within the centimetre level [14].

To evaluate registration accuracy, the study employed multiple methods. Quantitatively, the root mean square error (RMSE) between point cloud data before and after registration was calculated. The results indicated a significant reduction in RMSE after registration, confirming that the proposed method effectively decreased deviation between point cloud datasets. Qualitatively, comparisons between the registered point cloud data and actual building models were performed, focusing on consistency in detailed features such as building contours and the positions of doors and windows. These observations further validated the effectiveness of the registration method, as the registered data exhibited high consistency with real-world building models [15].

In addition to accuracy, the study emphasized registration efficiency, a critical concern given the large volume of urban building point cloud data generated by airborne LiDAR systems. To address this, an acceleration method based on a block strategy was proposed. The urban building area was divided into smaller blocks, with point cloud data registered separately in each block before integrating the results. Experimental findings demonstrated that this approach not only improved registration efficiency but also maintained registration accuracy to a satisfactory extent. Compared with traditional methods, the block strategy greatly reduced registration time, meeting the demand for rapid processing of large-scale urban point cloud datasets.

4. Discussion

Accuracy evaluation remains a crucial factor in assessing the effectiveness of point cloud registration methods. By combining quantitative RMSE analysis with qualitative feature consistency assessments, the study provides comprehensive evidence of the proposed method's reliability. The significant error reduction and strong alignment with actual building models illustrate the robustness of the improved ICP algorithm in handling complex urban environments, especially those with dense clusters of high-rise and structurally intricate buildings.

The adoption of the block strategy for registration acceleration offers a practical solution to the challenges posed by the sheer volume of airborne LiDAR data. This strategy strikes a balance between processing speed and registration accuracy, enabling efficient handling of large datasets without compromising the quality of the results. Such advancements are essential for scaling urban point cloud processing to real-world applications.

In practical terms, accurate airborne point cloud data registration technology holds great promise for supporting urban planning and architectural design. For urban planners, precise 3D models derived from accurately registered point cloud data provide an intuitive and reliable basis for decision-making. Meanwhile, architectural designers benefit from a better understanding of existing built environments, which aids in designing new structures that are more harmonious with their surroundings and tailored to actual needs. Overall, the study highlights the vital role of improved point cloud registration techniques in advancing urban development and design.

5. Conclusion

This study verified the application effect of airborne LiDAR point cloud registration technology in urban building environments through a series of experiments. The research results show that using the improved ICP algorithm for flight strip mosaicking can significantly improve registration accuracy and efficiency. By processing urban building point cloud data obtained at different time periods, it was found that the improved ICP algorithm can effectively reduce registration errors caused by factors such as changes in flight altitude and differences in attitude angles.

In the registration experiment of point cloud data obtained from multiple flight paths in the central area of a large city, when the traditional ICP algorithm was used, the average registration error reached about 0.3 meters; however, after introducing the pre-registration step based on feature matching, the final registration error was reduced to within 0.1 meters, which meets the requirements of urban level high precision 3D modeling. This achievement has laid a solid foundation for the subsequent large-scale urban 3D reconstruction work and also provided important technical support for other related fields such as unmanned driving navigation and intelligent traffic management. Future research should further explore more diversified feature extraction methods and how to better combine advanced technologies such as deep learning to further improve registration performance and expand its application scenarios.

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Disclosure statement

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