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The Application of Point Cloud Data Registration Algorithm Optimization in Smart City Infrastructure

Chuying Lu [1,*]

[1] University of Michigan, Ann Arbor, Michigan, 48109, USA
* Correspondence: Chuying Lu, University of Michigan, Ann Arbor, Michigan, 48109, USA

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Abstract: Point cloud data, as an effective carrier for storing higher-dimensional spatial information, plays an important role in promoting the realization of smart cities. However, variations in spatial information, collection methods, and densities among multi-source heterogeneous point cloud data significantly reduce the accuracy of modeling and perception. This paper focuses on core aspects of point cloud registration — feature extraction, improved ICP algorithms, deep learning-based registration models, and multi-source fusion methods — to enhance registration accuracy and robustness. This paper further explores the implementation of point cloud registration methods in areas such as urban traffic modeling, building and terrain renewal, facility monitoring, and urban planning. Precise matching algorithms provide fundamental algorithmic guarantees and data foundations for effectively enhancing the efficiency of multi-source data fusion and for urban spatial modeling, dynamic monitoring, intelligent scheduling, etc.

Keywords: point cloud registration; smart city; ICP optimization

1. Introduction

In the process of building a new type of smart city, precise perception and control of urban space is an important research direction. Point cloud data, as one of the most important forms of three-dimensional spatial representation, can effectively reflect the spatial information of a city's ground features, traffic routes, buildings, and facilities, thereby providing fundamental data support for the construction of the city information model and the operation of the city information system. However, due to the different usage and acquisition times of various types of sensors, there are often spatial position errors. Therefore, a matching algorithm needs to be applied to match all points. Although the traditional ICP algorithm is widely adopted, it has deficiencies in aspects such as initial pose sensitivity, local optimality, and low efficiency. To solve this problem, it is necessary to optimize the point cloud registration technology and provide ideas and references for the application of point cloud registration technology in the infrastructure of smart cities.

2. The Basic Principle of Point Cloud Data

2.1. Coordinate Acquisition

The first step of three-dimensional spatial modeling is the coordinate collection of point cloud data, that is, using sensor devices to obtain discrete points in an object or environment and record their spatial positions in the form of three-dimensional coordinates (X, Y, Z). Modern point cloud collection not only focuses on geometric information, but also often comes with multi-dimensional attributes such as color (R, G, B), reflection intensity, and timestamp, providing a data basis for subsequent semantic analysis and feature extraction. Common acquisition technologies include lidar, structured light, ToF cameras and 3D vision systems. Lidar, with its high precision and stability, acquires high-density point clouds by measuring the flight time and scanning angle of the laser and is widely used in outdoor modeling. Structured light generates depth information by projecting a grating and analyzing image distortion, which is suitable for small-range high-precision modeling [1]. ToF cameras calculate depth based on the phase or time delay of infrared signals, featuring high frame rates and low latency, and are often used for robot interaction. 3D vision simulates the double parallax of the human eye, acquires spatial information through image matching and triangulation, and is suitable for low-cost, multi-view mobile platform environments [1].

2.2. Registration Transformation

The core purpose of point cloud registration is to align the point cloud data collected from different sources and at different times uniformly into the same coordinate system to achieve the three-dimensional reconstruction of a complete scene or object. Registration is essentially a rigid body transformation problem. The goal is to achieve this without changing the geometric structure of the object. Find the optimal rotation matrix R and translation vector t between the source point cloud and the target point cloud. Minimize the geometric error between the two. Mathematically, this spatial transformation is usually expressed as:

$$P' = R \cdot P + t \tag{1}$$

Among them, P is the point in the source point cloud, and P' is the registered target point. The registration algorithm minimizes error functions, such as point-to-point and point-to-surface distances, through iterative computation. The error function usually adopts the sum of squares of Euclidean distances. When the initial pose deviation is large, point cloud registration is prone to fall into local optimum. Therefore, it is often necessary to improve robustness through feature matching, weight adjustment or global optimization. The quality of registration directly affects subsequent modeling and perception, and often plays a more critical role than the specific choice of registration algorithm. The current common methods include ICP with rigid registration, feature-based prior matching and deep learning models [2]. To enhance registration accuracy, some algorithms incorporate strategies such as point-to-surface distance constraints, directional vector constraints, and multi-scale processing. Registration, as a key link in 3D modeling and information fusion, is directly related to the efficiency of structural recognition, reconstruction and real-time perception of the urban environment [3].

3. Optimization Methods for Point Cloud Data Registration Algorithms

3.1. Feature Extraction and Matching

The core of the registration process lies in feature extraction and matching, aiming to improve the initial alignment accuracy and construct a robust correspondence between points. This process mainly addresses how to extract local or global geometric features from point clouds that can represent spatial differences and remain invariant under rotation. It is generally divided into three steps: Firstly, extract information such as surface normal and curvature within the local neighborhood of each point, and generate feature descriptors, such as FPFH, SHOT, SpinImage, etc., which have noise resistance and scale invariance; Secondly, efficient structures such as KD-Tree are utilized to conduct the nearest neighbor search of feature vectors in the target point cloud and establish the initial correspondence between the source point and the target point. Finally, the matching results are optimized by eliminating mismatched point pairs, estimating the coarse registration transformation, and combining algorithms such as RANSAC. This method can still provide reliable initial registration when the initial pose deviation is large or the viewing angle changes significantly, providing a stable starting point for subsequent algorithms such as ICP. It is suitable for high-precision point cloud alignment tasks in complex urban environments such as high-rise buildings and intersections [4].

3.2. Improved ICP Algorithm

The ICP algorithm is a commonly used basic algorithm for implementing the local configuration of point clouds. Its main idea is to continuously search for the optimal point pair set between two groups of point clouds through iteration, while simultaneously optimizing the geometric error using rigid transformations. Although the ICP algorithm has a fast operation speed and is easy to implement, it is relatively dependent on the initial pose and is prone to fall into local minima. In addition, its registration performance significantly degrades in the presence of noise, insufficient features, or sparse data. To this end, a variety of improvement strategies are proposed, among which the introduction of the point-to-plane distance error model is the most representative. The improved objective function is as follows:

$$\min_{R,t} \sum_{i=1}^{N} \left(n_i^T \cdot \left(q_i - (R \cdot p_i + t) \right) \right)^2 \tag{2}$$

Among them, p_i is a point in the source point cloud, q_i is the matching target point, n_i is the estimated normal vector at the target point q_i and R and t are the rotation matrix and translation vector to be determined respectively. This formula introduces surface direction information in error calculation. It not only emphasizes positional proximity between points but also ensures directional consistency, thus being more suitable for registration scenarios involving large planar structures, such as urban buildings and road boundaries. In addition, by combining multi-resolution iterative methods, weight error control and fast data organization (such as kd-Tree), it can also process massive urban point cloud data with greater stability and accuracy, while significantly improving computational efficiency, and be widely applied in smart city construction and facility perception.

3.3. Deep Learning Algorithms

In recent years, deep learning technology has provided excellent modeling and self-regulation capabilities for point cloud processing, and also offered new solutions for point cloud registration. Unlike manual feature description and recursive optimization, when deep learning completes point cloud registration, it utilizes an end-to-end network structure and can learn the spatial transformation relationship between the source point cloud and the target point cloud to achieve registration and adaptation. PointNetLK, DCP, and PRNet, as typical representatives, mainly consist of feature encoding networks, attention mechanisms, and transformation feedback components. They can extract complete and local information from the original input of the point cloud and directly output the optimal rotation and translation parameters, thereby completing the entire registration process. These methods have excellent stability and global adaptability for large-scale, sparse, noisy and nonlinear point clouds. At the same time, they can also meet the requirements of high registration accuracy and data consistency for multi-source point clouds of roads, buildings and equipment in complex urban environments. Some of these models support unsupervised or weakly supervised learning, simplifying registration labeling requirements and further enhancing practicality. In addition, by adopting the deep learning method, it can also be combined with the classic ICP algorithm to provide a more accurate initial solution for the initial alignment strategy, thereby improving the speed of the entire registration and the stability of the registration effect, and becoming the mainstream supporting technology based on the intelligent point cloud processing system [5].

3.4. Multi-Source Data Fusion

To improve the accuracy and robustness of point cloud registration in complex urban environments, multi-source data fusion has become a primary approach. Multi-source data fusion has been optimized for point cloud registration. The mainstream direction of its technical route is to strengthen spatial registration, enrich feature information and improve environmental adaptability. Higher precision global positioning of point clouds can be achieved through GIS data. RGB images provide higher texture detail and spatial semantics, while multi-temporal point cloud data supports dynamic change analysis and temporal modeling. From the perspective of feature extraction, fusing multimodal information significantly enhances the robustness and distinctiveness of local point cloud features, while collaborative learning with image data improves target recognition accuracy. Meanwhile, the inclusion of remote sensing data such as thermal imaging and synthetic aperture radar can solve the structural completion under occlusion and complex lighting conditions. For dealing with complex environments, the most crucial aspects are the consistency of coordinates from multiple data sources, the consistency of feature descriptions, the standardization of data formats, and the integration of filtering denoising and feature enhancement methods into the data, which can improve the registration accuracy under low-quality data (see Figure 1).

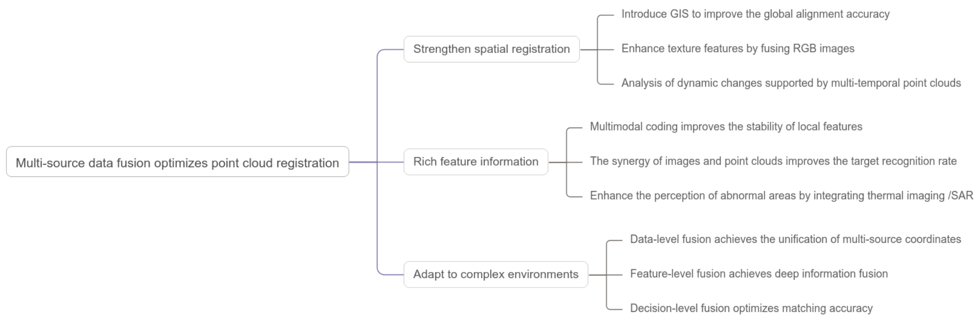

Figure 1. Multi-Source Data Fusion.

4. The Specific Application of 3-Point Cloud Data Registration in Smart City Infrastructure

4.1. 3D Modeling and Road Condition Monitoring in Intelligent Transportation Systems

Precise 3D modeling and real-time urban road perception are critical for the development of autonomous driving technologies, traffic control systems, and smart city management. With the widespread use of LiDAR, unmanned aerial vehicles, and onboard and roadside multi-modal sensors, real-time 3D coordinate data of streets, vehicles, and obstacles can be obtained. However, due to the differences in the perspectives, durations and densities of the information collected by different devices, spatial alignment deviations occur, affecting the modeling quality. Therefore, point cloud registration through feature extraction and improved ICP-based matching has become a key solution. By introducing a weighted point-to-plane distance and direction vector constraints, the alignment accuracy can be improved even under occlusion or noise interference, the alignment accuracy is improved in the case of occlusion or noise interference. Meanwhile, at the same time, deep learning models are used to automatically extract features such as lane markings, medians, and road signs, the ability of structural recognition and semantic modeling is further enhanced. Meanwhile, the multi-source fusion approach is simultaneously matched with GIS maps, camera videos, and traffic perception data to generate dynamic and information-rich urban digital traffic models.

4.2. High-Precision Construction and Update of Urban Architecture and Terrain Models

Point cloud information is an important means for 3D modeling and is widely applied in aspects such as digital twin cities, CIM, urban model planning, asset management, and urban disaster analysis. In order to achieve the requirement of high accuracy for this modeling, it is necessary to integrate airborne lidar, ground laser scanning, and vehicle-mounted mobile measurement to obtain point cloud data of different densities, high-resolution photos, and their three-dimensional point clouds. At the same time, it is necessary to overcome registration challenges caused by equipment limitations, such as varying density, time misalignment, and occlusions during data acquisition caused by the measurement accuracy of the equipment. High-precision registration is obtained by means of the optimized point cloud registration algorithm. Common strategies include enhancing features to improve registration accuracy, applying elastic transformation fitting methods, and using deep learning models such as DCP and PointNetLK to enhance the reliability of high-density point cloud alignment. After concentrating these different point clouds, small-scale building features such as building surfaces, roofs, their complex shapes and terrain slopes can be precisely expressed through point cloud data, and it can provide strong database support for digital twin cities and real-time urban planning. The continuous registration of multi-temporal point clouds can also be utilized to achieve real-time monitoring of new buildings, illegal constructions and land changes, thereby supporting real-time updates to urban spatial data (see Table 1).

Table 1. High-Precision Construction and Update of Urban Architecture and Terrain Models.

Application link	Technical means	Practical effect
Data acquisition	Aerial lidar, ground laser scanning, vehicle-mounted mobility	Obtain point cloud data of different densities, high-resolution photos and their three-dimensional point clouds
Registration method optimization	Feature enhancement, the use of elastic transformation fitting method and deep learning	Improve the registration accuracy and enhance the reliability of high-point cloud registration
Improvement of modeling accuracy	Accurately express small-scale architectural features such as building surfaces, roofs, their complex shapes and terrain slopes	It provides strong database support for digital twin cities and real-time urban planning
Time series data fusion	Continuous registration of multi-temporal point clouds	Real-time monitoring of new buildings, illegal constructions and land changes

In conclusion, multi-source fusion and registration optimization technologies have greatly expanded the applicability and application scope of point clouds in complex urban areas, and they are important supports for the management of refined smart cities.

4.3. Optimization of Monitoring and Management of Public Facilities

Key urban infrastructure such as bridges, subway entrances, sewage pipelines, and communication cables are prone to aging, corrosion, mechanical wear, or foundation deformation. These issues can lead to safety hazards such as cracking, misalignment, or structural deformation. Therefore, establishing a precise and effective real-time and efficient digital-analog monitoring network has become a critical objective in modern urban monitoring and infrastructure management. 3D point cloud data is widely adopted in structural evaluation and equipment condition monitoring due to its non-contact nature, precise localization capabilities, and comprehensive spatial representation. The three-dimensional point clouds of the equipment are collected at regular intervals. Effective registration techniques are used to align point clouds collected at different time intervals, enabling quantitative analysis of local shape changes, and the local shape changes are quantitatively analyzed. To enhance the registration performance, normal constraints and weight error constraints are added to the traditional ICP algorithm to improve the matching effect of complex parts and edges. The graph optimization algorithm is utilized to complete the global consistent registration of large-scale equipment. By integrating the registration results into the BIM model, it becomes possible to visualize structural changes at the component level, including the determination of hazard points and support timely maintenance and decision-making.

4.4. Resource Optimization and Allocation in Smart City Planning

The core of intelligent city planning lies in achieving the rational scheduling and efficient allocation of urban spatial resources. The latter requires high-quality three-dimensional spatial information as the basis for scientific and reasonable planning. Firstly, data from various sources and shapes are aligned and accurately registered through point cloud data to achieve the unified coordination of spatial information on each platform, eliminate data deviations, and build the foundation of three-dimensional perception. Secondly, point cloud data supports diverse spatial analyses — including building volume estimation, population density evaluation, land use modeling, and green space ratio calculations — which contribute to optimizing the layout of urban functional clusters to provide support for promoting the improvement of the layout of urban functional clusters and enhance the scientific nature of the overall layout and configuration. Furthermore, based on multi-temporal point clouds and deep learning models, supporting urban development trend prediction, post-disaster recovery, ecological protection, and infrastructure adjustments such as road widening, to enhance its ability to adapt to complex environments and evolve governance and management (see Figure 2).

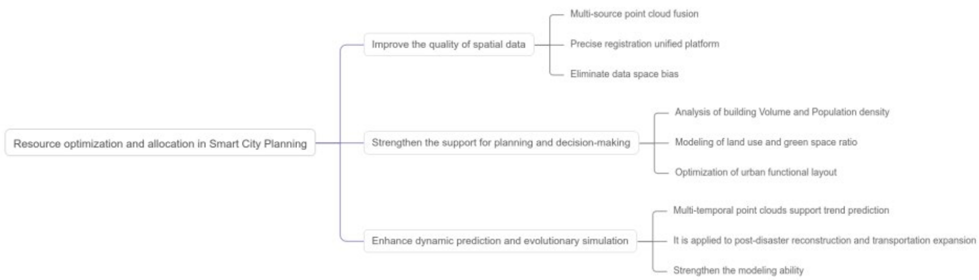

Figure 2. Resource Optimization and Allocation in Smart City Planning.

5. Conclusion

For building a three-dimensional information model of a smart city, point cloud data is an indispensable basic data, and the registration accuracy of point cloud data is the key to the success or failure of subsequent model construction, monitoring and analysis. Starting from the principle of point cloud collection and registration, through the analysis of optimization methods based on feature extraction, ICP improvement, deep learning and multi-source fusion, this paper discusses the key application situations of the above methods in practical fields such as traffic modeling, building reconstruction, facility management and planning support. This integrated approach improves the efficiency and accuracy of data synchronization by incorporating multiple advanced algorithms. By significantly enhancing the utility of point cloud data, registration techniques — supported by AI and real-time sensing — are poised to exert greater influence in fields such as smart city digital twins, autonomous transportation, and urban operations.

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