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Improvement of ICP Point Cloud Splicing Technology in the Detection of Tunnel Diseases in Shield Tunnels

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Abstract

With the rapid development of urban underground transportation projects, shield tunnels have become integral components of urban transportation systems. However, shield tunnels may be subject to various factors during their long-term operation, leading to structural diseases and damage. Therefore, accurate tunnel disease detection technology is crucial for the maintenance and management of tunnels. This paper introduces an improved Iterative Closest Point (ICP) point cloud registration technique and applies it to the detection of diseases in shield tunnels. By utilizing KD-tree for point cloud matching, this study significantly enhances both the accuracy and efficiency of point cloud registration. In experiments, we successfully apply this technique to real-world shield tunnel data, achieving precise disease detection and high-quality point cloud registration.

Keywords

Point cloud splicing; ICP; Shield tunnel; Disease detection.

1. INTRODUCTION

The structural condition of tunnels directly impacts the safety and reliability of urban underground transportation and infrastructure[1]. Therefore, the detection of diseases in shield tunnels has consistently remained a significant concern in both research and engineering practice[2]. Traditional detection methods typically involve visual inspections and physical testing; however, these methods face several limitations, such as the inaccessibility of the tunnel's interior environment and the inability to access certain surfaces. Point cloud data acquisition technology has emerged as a potent tool for disease detection in shield tunnels, enabling non-contact and high-precision acquisition of three-dimensional information within the tunnel[3]. As a result, point cloud data has become a critical data source for modern shield tunnel disease detection.

Point cloud data processing plays a pivotal role in achieving disease detection in shield tunnels[4]. Point cloud data usually exists in large-scale and high-density formats, necessitating processing, analysis, and visualization. In point cloud data processing, point cloud registration and alignment are critical tasks[5-6]. The traditional Iterative Closest Point (ICP) algorithm has been the prevailing method for point cloud registration, achieving alignment between point clouds through iterative nearest neighbor searching. However, traditional ICP algorithms encounter challenges related to high computational complexity and low matching efficiency

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when dealing with large-scale point cloud data. Consequently, there is a need for more efficient and precise point cloud registration methods.

While traditional point cloud alignment methods like the Iterative Closest Point (ICP) algorithm[7] have been widely applied for point cloud registration tasks, they exhibit limitations in terms of accuracy and efficiency when processing large-scale point cloud data. To address these limitations of the traditional ICP algorithm, this study introduces an improved ICP point cloud registration technique. This technique enhances the accuracy and efficiency of point cloud matching by incorporating the KD-tree (KD-Tree) data structure[8]. The KD-tree is an efficient data structure that accelerates nearest neighbor searches, thereby increasing the speed of point cloud matching. The improved ICP model utilizes the KD-tree to search for nearest neighbor points, resulting in more precise establishment of correspondences between point clouds. This improvement not only promises enhanced point cloud alignment accuracy but also expedites the alignment process. We apply this technology to shield tunnel point cloud data to achieve more accurate disease detection and structural reconstruction.

2. METHODOLOGY

There are several methods for point cloud registration, which can be categorized into two main types based on the primitives used during registration: feature-based registration and non-feature-based registration[9-10]. Feature-based registration can be further subdivided into target point registration, common feature point registration without targets, and mixed methods. Non-feature-based registration often employs the ICP (Iterative Closest Point) algorithm.

2.1. Traditional Point Cloud Registration Techniques

Feature-based registration methods initially involve identifying conspicuous common feature points between adjacent station point cloud data. These feature points can be target spheres, targets, corner points, etc. By utilizing these feature points, we can further calculate the registration parameters to effectively align the point cloud data.

2.1.1. Target Sphere (Target) Registration

This approach employs target spheres (or targets) as well as known coordinate points as common feature points. During on-site data collection, target spheres (or targets) are placed at suitable positions within the scanning measurement area. It is important to avoid arranging the target spheres in a straight line and instead distribute them evenly while ensuring that there are at least 3 or more common target spheres between adjacent stations.

2.1.2. Same-Name Feature Point Registration

This method shares fundamental principles with target sphere (target) registration but does not require the placement of target spheres during on-site data collection. During the post-processing stage of point cloud registration, distinctive common feature points are manually selected between adjacent stations and assigned the same name. Typically, these feature points are chosen at corners, wall junctions, and locations with distinct features like signage. However, unlike traditional single-point measurement methods, laser scanners do not actively scan and collect data from specific individual points. Due to factors such as resolution settings, laser scan lines acquire point cloud data at specific intervals, and the laser beam spot is not a single point. Consequently, manually selecting feature points may not accurately match into pairs of same-name points. This manual feature point selection introduces significant errors, resulting in relatively lower registration accuracy and efficiency.

These feature-based registration methods play a crucial role in point cloud data processing but necessitate consideration of the accuracy of feature point selection and matching. Particularly in the case of same-name feature point registration, where manual selection of

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feature points can introduce significant errors, future research directions may include enhancing feature point selection and matching algorithms to improve registration accuracy and efficiency.

2.2. Traditional ICP Algorithm

In comparison to the feature-based registration methods discussed in this paper, non-feature-based registration methods do not require the placement of target spheres or targets within the scanning area, nor do they involve manual selection of common feature points. Typically, they are based on the Iterative Closest Point (ICP) algorithm proposed by Besl and McKay, which is an iterative least-squares optimization process used to find the best rigid transformation between two adjacent point cloud datasets[11].

The traditional ICP algorithm iteratively optimizes the transformation matrix. Each iteration includes the following steps:

Corresponding Point Matching: Initially, it establishes correspondences between points by finding the nearest neighbor for each point in the source point cloud.

$$q_i = argmin_j ||p_i - q_i|| \tag{1}$$

Where: p_i is the ith point in the source point cloud; q_i is the nearest neighbor point in the target point cloud corresponding to p_i.

Computing the Best Transformation: Next, it uses the least-squares method to estimate the best transformation matrix T that minimizes the distance between points.

$$T = argmin_T \sum_{i=1}^{N} ||T.p_i - q_i||^2 \tag{2}$$

Where: T is the transformation matrix that aligns the points from the source point cloud to the position and orientation of the target point cloud; p_i is the ith point in the source point cloud; q_i is the corresponding point in the target point cloud; N is the total number of points in the point cloud.

Applying the Transformation: It transforms the source point cloud to its new position:

$$p_i' = T.p_i \tag{3}$$

Where: p_i is the ith point in the transformed source point cloud; T is the optimized transformation matrix; p_i is the ith point in the source point cloud.

Convergence Detection: These steps are repeated until a convergence condition is met (e.g., the change in the transformation matrix is smaller than a threshold).

2.3. Improved ICP Algorithm

In this section, we propose an improved ICP algorithm aimed at enhancing the accuracy and efficiency of point cloud matching. The primary improvement lies in the introduction of the KD-tree data structure to enhance nearest neighbor search in point clouds. The KD-tree is an efficient data structure that significantly improves the speed of point cloud matching.

2.3.1. KD-tree Construction

First, we construct a KD-tree for the target point cloud. The KD-tree is a binary tree structure in which each node represents a point, recursively dividing the point cloud data into subsets for

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rapid nearest neighbor searches. The process of constructing the KD-tree can be represented as follows:

$$\boldsymbol{BuildKDTree}(\boldsymbol{P}, \boldsymbol{depth}) \tag{4}$$

Where $\boldsymbol{P}$ is the point cloud data, and $\boldsymbol{depth}$ represents the tree's depth. By continuously partitioning the point cloud data, we create an efficient KD-tree.

2.3.2. KD-tree Search

In each iteration of the improved ICP algorithm, we use the KD-tree to search for the nearest neighbor of each point in the source point cloud. This can be achieved as follows:

$$\boldsymbol{q_i} = \boldsymbol{FindNearestNeighbor}(\boldsymbol{p_i}, \boldsymbol{KD\_Tree}) \tag{5}$$

Where $\boldsymbol{KD\_Tree}$ represents the $\boldsymbol{KD\_Tree}$ of the target point cloud. This efficient nearest neighbor search method significantly improves the efficiency of point cloud matching.

2.3.3. Improved Transformation Estimation

In the improved ICP algorithm, we still use the least-squares method to estimate the best transformation matrix T to minimize the distance between points, similar to traditional ICP.

$$T = argmin_T \sum_{i=1}^{N} ||T.p_i - q_i||^2 \tag{6}$$

Where: T is the transformation matrix that aligns the points from the source point cloud to the position and orientation of the target point cloud; p_i is the ith point in the source point cloud; q_i is the corresponding point in the target point cloud; N is the total number of points in the point cloud.

3. EXPERIMENTAL ANALYSIS

3.1. Experimental Design

To assess the performance of traditional ICP and the improved ICP model in point cloud registration for shield tunneling in a highly controllable and comparable manner, the following steps were taken:

(1) Data Acquisition: Three sets of shield tunnel point cloud data were acquired using a laser scanning device. Each data set consisted of two adjacent point clouds to ensure a comprehensive experimental dataset.

(2) Point Cloud Preprocessing: Before point cloud registration, data preprocessing was conducted, including denoising, coordinate transformation, and downsampling, to ensure data quality consistency.

(3) Traditional ICP Point Cloud Registration: Point cloud registration was performed using the traditional ICP algorithm, treated as the control group in the experiments.

(4) Improved ICP Point Cloud Registration: The same point cloud data were registered using the improved ICP algorithm, treated as the experimental group.

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(5) Comparison of Registration Results: A comparison was made between traditional ICP and improved ICP models' point cloud registration results on the three sets of experimental data to assess their performance differences.

3.2. Experimental Data Acquisition

The primary objective of this paper is to validate the potential application of the improved ICP model in shield tunnel disease detection. To achieve this goal, a 3D laser scanner was employed in a station-based manner, resulting in a total of six point cloud datasets with a density of 3mm each. These datasets were divided into three groups, namely DG_1, DG_2, and DG_3, with each group consisting of two adjacent point clouds. By comparing the point cloud registration results of traditional ICP and improved ICP on these three sets of experimental data, we aimed to evaluate the effectiveness and performance of the improved model.

3.3. Evaluation Metrics

To evaluate the accuracy of different methods in point cloud registration, we used the Root Mean Square Error (RMSE) as the evaluation metric. The RMSE was calculated as follows:

$$RMSE = \sqrt{\frac{1}{N_p}\sum_{i=1}^{N_p} ||Rp_i + T - q_i||^2} \tag{7}$$

Where: N_prepresents the number of corresponding point pairs; p_i denotes a point in the source point cloud; q_i represents the corresponding point in the target point cloud.

The RMSE quantitatively measures the precision of the registration, with smaller RMSE values indicating better alignment accuracy. This metric allows us to assess the accuracy of different registration methods and further evaluate their performance and effectiveness.

3.4. Experimental Results and Analysis

Table 1. Comparative Analysis of Registration Accuracy with Different Methods

Experimental Group	Traditional ICP RMSE	Improved ICP RMSE
DG_1	0.023	**0.012**
DG_2	0.032	**0.014**
DG_3	0.028	**0.011**

From Table 1, it can be observed that the improved ICP model demonstrates lower RMSE values in all experimental groups compared to traditional ICP. This indicates that it can more accurately register point cloud data, offering a significant advantage in reconstructing shield tunnel structures.

In addition to accuracy, we also compared the computational efficiency of the registration models. We measured the average time required to register each set of point clouds and compared the registration speeds of the two models. Table 2 shows the average registration times for different models.

Table 2. Comparative Analysis of Registration Time with Different Methods

Experimental Group	Traditional ICP RMSE	Improved ICP RMSE
DG_1	32.7	**21.5**
DG_2	35.2	**22.8**
DG_3	34.1	**23.4**

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From Table 2, it can be observed that the improved ICP model also exhibits a significant advantage in point cloud registration efficiency, with significantly shorter average registration times compared to traditional ICP. This is of great significance for processing large-scale shield tunnel point cloud data.

As shown in Figure 1, blue represents the target point cloud, and orange represents the source point cloud. From the figure, it can be seen that the improved ICP model achieves a better registration effect on shield tunnel point clouds compared to the traditional ICP model. The introduction of the KD-tree data structure greatly improves point cloud matching speed and accuracy, resulting in a closer alignment between the source and target point clouds. This overall enhances the quality of shield tunnel point clouds, providing support for the quality of disease detection outcomes.

The experimental results and analysis demonstrate that the improved ICP model outperforms the traditional ICP model in terms of both accuracy and efficiency when registering shield tunnel point clouds.

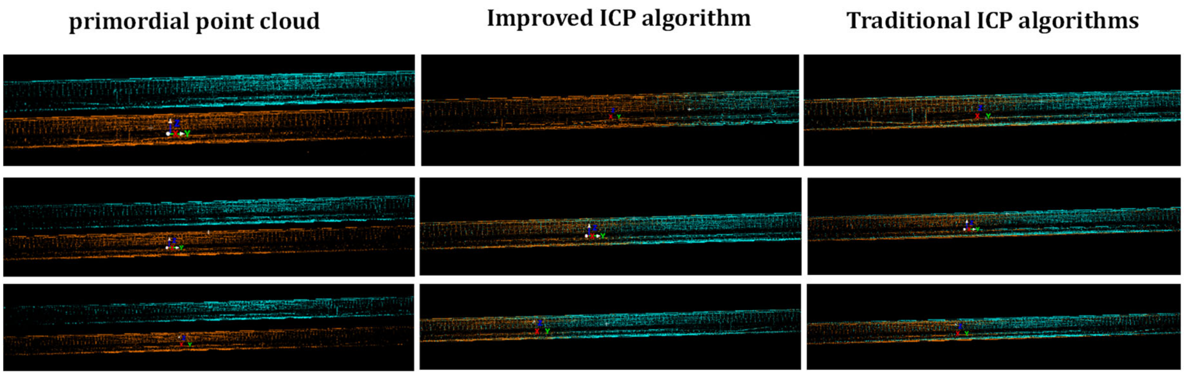

Figure 1. Point Cloud Registration Visualization Results

4. CONCLUSION

In conclusion, this study rigorously evaluated the performance of traditional ICP and the improved ICP model in registering shield tunnel point clouds through a carefully designed experimental approach. The experimental results demonstrate that the improved ICP model outperforms the traditional ICP model in both registration accuracy and efficiency. Its higher accuracy and shorter computation time make it a powerful tool for shield tunnel disease detection. The successful application of this research provides a feasible technical solution for the maintenance and management of urban underground transportation engineering and offers new perspectives and directions for further research in the field of point cloud registration.

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