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The Review of Research on 3D Model Reconstruction Based on Point Cloud Data

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Abstract. Point cloud-based 3D modeling is a cutting-edge technology that leverages point cloud data from sensors like lidar and cameras to recreate detailed 3D models of objects and environments. This paper serves to outline the fundamental route, key principles, and prevalent methods within this field, with a specific emphasis on the preprocessing registration techniques for point cloud data and the advancements in 3D model reconstruction technologies.Furthermore, the article will delve into foundational 3D reconstruction methodologies, categorizing them into optimization-driven approaches and interpolation or fitting strategies. By categorizing these methods, it becomes possible to address the limitations and challenges associated with each algorithm and propose potential enhancement strategies to overcome these obstacles.By refining existing techniques, developing novel methodologies, and enhancing computational efficiency, the future holds promise for significant advancements in the realm of 3D modeling through point cloud data. In the conclusion, we provide a summary and outlook for the entire paper.

Keywords: 3D Model Reconstruction; Point Cloud; Comparison of methods; Classification.

1. Introduction

With the rapid progress of sensor technology, such as the popularization of 3D scanning, lidar and camera equipment, obtaining large-scale point cloud data has become increasingly convenient and cost-effective, which provides rich input data for 3-D model reconstruction, which makes 3-D model reconstruction technology become a research hotspot and presents a wide range of application potential.

Point cloud data constitutes a collection of points obtained by sensors in space, where the coordinates of these points accurately describe the surface of objects in the real world. Processing and analyzing point cloud data enable the reconstruction of three-dimensional models of real-world objects, which finds wide applications in engineering design, digital cultural heritage preservation, virtual reality, among other fields. 3D model reconstruction of point cloud data has important research significance and practical application value in the field of computer vision and computer graphics.

The main focus of this paper will be on the technology of reconstructing 3D models from point cloud data, including its general technical route, basic principles, common methods and application scenarios. And focus on the basic principle comparison and optimization of 3 D reconstruction algorithms. This paper will introduce some basic 3 D reconstruction methods and divide them into two categories: optimization-based methods and interpolation-based or fitting methods. Then, the shortcomings of various algorithms and the improved schemes are discussed on the basis of classification.

2. 3D model reconstruction algorithm based on point cloud data

The general technical route of point cloud 3 D reconstruction algorithms usually includes three steps. The first is the preprocessing phase, whose main purpose is to eliminate erroneous data or process the sampling points to reduce the time cost of subsequent calculations.

The second is the two-dimensional linear graph construction stage. By constructing a two-dimensional linear graph, we have the ability to describe the spatial relationship between neighboring parts of the surface, perform global sorting, and take into account potential constraints. This stage can be seen as an abstraction and representation of point cloud data to provide a clearer data structure and topological relationships for subsequent 3 D reconstruction.

This is followed by a 3 D reconstruction. Generating polygonal surfaces is the core step of 3 D reconstruction, which involves creating a triangle or tetrahedral mesh to meet some quality requirements, such as limiting the size of the mesh elements and avoiding the intersection of broken lines. At this stage, through further processing and optimization of the 2 D linear graph, the 3 D surface model that meets the requirements is finally generated, and the 3 D reconstruction of the whole point cloud is completed.

2.1. Point cloud preprocessing

Cloud data pre-processing registration is a key step in point cloud processing, including multi-angle acquisition of point cloud splicing, denoising, and semantic segmentation. In point cloud splicing, common methods include Point Feature Histograms (PFH), Fast Point Feature Histograms (FPFH) normal distribution transformation and ICP point cloud registration. Point Feature Histograms and Fast Point Feature Histograms are commonly used point cloud feature descriptors for point cloud registration. These methods describe point cloud data by computing local geometric features for each point, facilitating the alignment of point clouds. The process involves estimating normals for each point, calculating a set of feature values within the neighborhood of each point (such as differences in normals' angles or curvatures), constructing a histogram based on these values as the feature descriptor for the point, comparing feature histograms of different points to assess their similarity, and applying registration algorithms to optimize the alignment between point clouds. PFH and FPFH methods are widely used in point cloud registration and object recognition, effectively capturing local geometric features of point clouds to enhance registration accuracy and stability.

3D normal distribution transformation (NDT) is a common point cloud registration method, whose main idea is to transform the dense 3D point cloud data into a probability distribution known as the NDT unit, aiming to offer a more efficient representation of geometry. In NDT, each NDT unit represents the statistics of the point cloud data within a local region, usually including the mean and covariance matrix [1]. These statistics can describe the spatial distribution and shape characteristics of point clouds within this region, thus enabling the effective modeling and description of point cloud data. The NDT method is suitable for point cloud registration in complex environments, and can improve the accuracy and robustness of the registration. Figure 1 outlines the step-by-step process of point cloud data registration. Initially, data preparation is carried out, involving input and target point cloud data. Next, feature extraction is performed to compute characteristics like normal vectors and curvature for each point cloud. Finally, the point cloud data is converted into a mesh format, and NDT algorithm parameters are initialized; following that, NDT matching is carried out, calculating the transformation matrix for every point within the input point cloud data is matched with the most suitable point in the target point cloud data; thereafter, the registration results are evaluated based on the similarity between matching points, and an optimization algorithm is used to further refine the matching results; finally, the transformation matrix is output to align the input point cloud data with the target point cloud data.

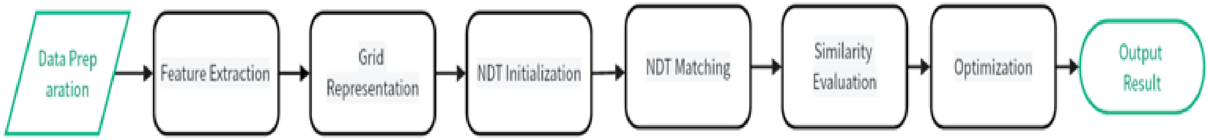

Fig. 1 Flowchart of NDT (Photo/Picture credit :Original)

ICP is a classical point cloud registration algorithm, which continuously iteratively optimizes the estimated transformation parameters to minimize the distance between two point clouds to achieve their registration. The ICP algorithm is simple and intuitive, and it is extensively utilized for point cloud registration, map construction and other fields. The greatest advantage of the ICP algorithm the greatest advantage is that the results are very stable and reliable. Disadvantages such as the low computational efficiency, the high overlap rate of the two data sets, the computation time is too long, prone to getting trapped in local optimal solutions. Figure 2 summarizes the core steps of the ICP algorithm: correspondence point selection, distance measurement, parameter optimization, and convergence check. Firstly, based on the initial transformation matrix, corresponding points between the first and second point clouds are identified to calculate the distance error. Secondly, the mismatch between the two point clouds is measured by computing the distances between corresponding points. Then, mathematical optimization methods like least squares are used to adjust the transformation matrix and minimize the distance error through iterative parameter updates. Finally, after each iteration, a convergence check is performed to determine whether to terminate the algorithm or continue with the next iteration based on stopping criteria such as reaching a sufficiently small error or the maximum number of iterations.

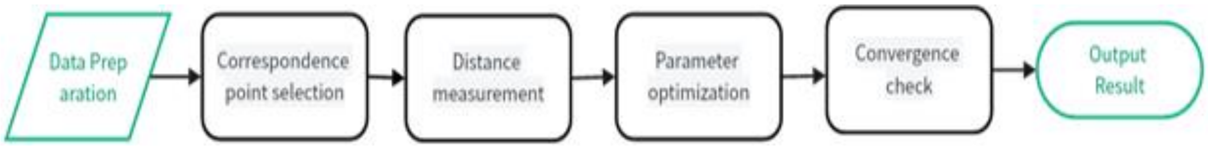

Fig. 2 Flowchart of ICP (Photo/Picture credit: Original)

The denoising process usually uses a voxel mesh filtering method to eliminate the interference of noise points to subsequent treatments. Vvoxel grid filtering is a technique commonly used in point cloud processing to solve the problem of uneven point cloud density by mapping point cloud data into a three-dimensional voxel grid structure. Through the rapid query function of the voxel grid, the selection range of calculation points can be limited while filtering out the redundant points on the same surface, thus reducing the ambiguity in the building registration or reconstruction process and improving the accuracy and stability of the results. Moreover, voxel mesh filtering can also accelerate the processing process and improve the computational efficiency, especially in large-scale point cloud data processing. But for non-uniformly distributed point cloud data, it may lead to the loss or inaccuracy of information.

Furthermore, models that require semantic segmentation or classification, methods such as principal component analysis (PCA) can be applied [2]. Semantic segmentation, on the other hand, can help distinguish the semantic information of different parts of the point cloud, which helps further data processing and analysis. By employing a combination of these preprocessing techniques, the quality and accuracy of the point cloud data can be significantly improved. This lays a solid foundation for subsequent 3D reconstruction and analysis tasks.

2.2. Two-dimensional linearized map construction

Two-dimensional linearized map construction refers to the conversion of point cloud data in three-dimensional space into a linear representation on a two-dimensional plane. In 2D linear map construction, feature extraction of the point cloud and the production of each view of the modeling are required. In order to improve the fitting accuracy, Victor Sanchez and Avideh Zakhor used the RANSAC algorithm to extract models that conform to specific geometries (e.g. planar, rectilinear) from the raw 3D point cloud data, obtaining results with high fitting accuracy [3].Their suggested system, incorporating model-fitting and RANSAC, demonstrates the ability to identify both large-scale architectural elements like ceilings and floors, and small-scale features such as staircases. Besides, Shima Sahebdivani et al. similarly used the RANSAC algorithm to line-fit filtered candidate points in the point cloud and identify final points associated with the rails to support subsequent modeling [4]. RANSAC The basic idea of the RANSAC algorithm is to estimate model parameters by randomly sampling a small number of data points and use these parameters to determine whether other data points fit the predefined model. By iteratively applying the RANSAC algorithm, it can efficiently distinguish between inliers (data points conforming to the model) and outliers (data points deviating from the model), thereby achieving more precise estimation of model parameters. In each iteration, it was decided whether to terminate or continue the iteration by comparing the inner point proportions and predefined thresholds.

A big advantage of the RANSAC algorithm is that it also produces good estimates for data sets containing a large number of outliers. By setting the appropriate number of iterations and inner point threshold, the robustness of the algorithm and computational efficiency can be balanced.

On this basis, the ELISAC method proposed by Bahram Salehi et al. is an improvement to the traditional RANSAC algorithm, aiming to improve its stability and accuracy. ELISAC employs three key modifications to optimize the performance of the RANSAC algorithm. First, ELISAC introduces two types of local iterative least squares loops, basic LILS and aggregated LILS, which are capable of adjusting the parameters of the model according to the newly found outliers in each round of iterations, thus improving the stability and accuracy of the fit. Second, ELISAC reduces the number of iterations by improving the convergence speed and introducing a similarity termination criterion, which accelerates the convergence speed of the algorithm and improves the efficiency of the algorithm while maintaining high accuracy of the fitting results. Finally, a post-processing procedure is introduced in ELISAC to identify and eliminate outliers that may exist at the end of the loop. This step can further improve the reliability of the final fitting results and ensure that the output results are more robust and accurate [5].

2.3. Three-dimensional reconstruction

Based on point cloud data, three-dimensional reconstruction involves extracting information from the point cloud, combining it with other data sources, and establishing connection relationships between these points to mathematically construct and digitally represent an object. There are many mature methods for 3D reconstruction based on point cloud, such as Poisson surface reconstruction, piecewise energy method, local bicubic interpolation method, 3D reconstruction algorithm based on Delaunay triangulation, and 3D reconstruction algorithm based on radial basis function, etc. In this paper, these methods are mainly classified into optimization-based methods and interpolation or fitting-based methods.

2.3.1. Methods Based on Optimization

The methods based on optimization include Poisson surface reconstruction and shding energy method. The basic principle of Poisson reconstruction is to calculate the gradient of the surface using the normal information of the discrete point cloud data, and to use this information to construct the Poisson equation. A continuous, smooth surface representation can be obtained by solving the Poisson equation. The advantage of this method is that it can handle irregular and incomplete point cloud data, which requires low data quality, and is often applicable to recover smooth surface models from sparse point cloud data.

The shding energy method simplifies the problem by splitting the raw data into small blocks and constructs using energy minimization. In the shding energy method, the point cloud data is first converted into the initial state of the surface grid, and then the control vertices of the surface grid are grouped. The control vertices of each group represent the shape and features of the surface in the local regions. The energy of a surface is usually defined by geometric features and constraints such as curvature and smoothness, etc. Therefore, by gradually optimizing the position of the vertex, the energy of the surface can be continuously reduced, thus making the surface smoother and meeting the characteristics of the original point cloud data. This procedure is usually an iterative optimization process that can use numerical optimization methods to control the position of the verx to minimize the energy function of the surface. Song Junfang et al used piecewise energy generation to reconstruct the surface's optical smoothness. The surface smoothing problem is transformed into an unconstrained optimization problem, but since this algorithm has a tendency to turn the surface into a planar one. Moreover, the mathematical expression formula and the amount of computation are cumbersome, so the team subsequently switched to the local double cubic surface interpolation method for modeling [6].

2.3.2. Interpolation or Fitting-Based Methods

Based on the interpolation or fitting method, there are mainly localized double cubic surface interpolation, 3D reconstruction algorithm based on Delaunay triangular section and 3D reconstruction algorithm based on radial basis function. Localized Double Cubic Surface Interpolation fits surfaces by using double cubic interpolation functions in a local region. This method can better maintain the smoothness and continuity of the data in a localized region, and is suitable for cases where surface fitting to local data is required. For example, Song Junfang et al. used the bicubic interpolation method for 3D reconstruction of blade profiles based on laser point cloud data. By interpolating a given point cloud of profile values, a bicubic NURBS surface is constructed, which maintains geometric first-order continuity in both the U and V directions[6].

Triangulation is a process of converting a given set of points into a coherent polygonal model, or mesh. In this process, the input data is divided into simple geometric elements, usually including vertices, edges, and faces, and these geometric elements represent the surface or region being analyzed. In the finite element method, the measurement domain is divided into many small "elements," typically triangles or quadrilaterals in 2D and tetrahedra in 3D. Optimal triangulation is defined based on the angles, edge lengths, heights, or areas of the elements, with errors in finite element approximations often related to the minimum angles of the elements. The vertices of the triangulation can be input points or additional points called Steiner points, inserted to create a more optimal grid. Triangulation can be performed in either 2D or 3D, depending on the geometric shape of the input data [7].

3. Advantages and Disadvantages of each method

So far, there are some disadvantages of 3D reconstruction algorithms for point cloud data as follows: the Poisson surface reconstruction is more sensitive to the noise in the input point cloud, which may lead to irregularities in the generated surface models areas in the input point cloud. The computation time is prolonged due to the computational complexity, particularly when coping with large-scale point cloud data. The piecewise energy method may be trapped in local optimal solutions and may not result in a globally optimal surface model. The energy function and parameter settings have a large impact on the surface reconstruction results, and it is difficult to adjust the parameters for specific applications. The double-cubic interpolation method is sensitive to the sampling and distribution of the local data. Inadequate or non-uniformly distributed local data can significantly impact its accuracy, it may lead to inaccurate surface interpolation results and overfitting, especially when the local data are noisy or the sampling density is not uniform enough. The 3D reconstruction algorithm based on radial basis function needs to solve large linear equations, which will increase the value of the extra distance field function of the points, resulting in low computational efficiency and ineffective noise suppression. The 3D reconstruction algorithm based on Delaunay triangulation has a long computation time and limited noise reduction capability. Three-dimensional reconstruction models sometimes form holes, which are usually simply fixed with triangles, and although the data near the holes are fitted with a global smooth continuous radial basis function, the closed angles cannot be fitted. So many researchers have proposed improved methods based on this. Advantages and Disadvantages of Different 3D Reconstruction Methods are listed in the table 1 below:

Table 1. Advantages and Disadvantages of each method

Method	Advantages	Disadvantages
Poisson Surface Reconstruction	- Smooth surface models - Handles irregular point cloud data	- Sensitive to noise - High computational complexity
Piecewise Energy Method	Smooth surface models - Addresses local optima	Dependent on energy function and parameters - May get stuck in local optima
Double-Cubic Interpolation Method	Accurate surface interpolation Suitable for local data	Sensitive to data sampling and distribution - Prone to overfitting
Radial Basis Function 3D Algorithm	Generates 3D models - Offers some noise suppression	Requires solving large equations - Limited noise reduction capabilities
Delaunay Triangulation 3D Algorithm	Creates 3D models - Can fill holes and use global smoothing	Long computation time - Limited noise reduction - May result in holes needing patching

4. Improvement of methods

4.1. Mechanism and Topology Consideration

Chen Kai and other researchers proposed a three-dimensional reconstruction method of laser helical scanning point cloud. Since the 3D reconstruction method of laser helical scanning point cloud considers the mechanism and topology of the point cloud, it is consistent with the point cloud being sharp and without holes. After using these methods to process the point cloud, there is no need to spend time traversing the entire point cloud, the algorithm is efficient, and all the point clouds will participate in the 3D construction, while the 3D construction model does not have any holes [7].

4.2. Utilization of Deep Learning Techniques

By integrating deep learning techniques, it becomes feasible to capture both local and global features of point cloud data, leading to the generation of superior reconstruction results For example, PointNet and PointNet++ are two commonly used deep learning models, which can be used to learn the feature representation and reconstruction of point clouds in an end-to-end manner. There are also well-researched review articles in the related fields, for example, Wenpei et al. introduced the current status of the research on point cloud classification methods, and then focused on the main and the latest methods of point cloud classification based on deep learning. The point cloud classification methods are categorized according to the way of data processing, the main ideas, advantages and disadvantages of each type of method are summarized and compared, and the implementation process of some representative and innovative algorithms is described in detail [8].

4.3. Global Optimization Algorithms

Global optimization algorithms such as genetic algorithm and simulated annealing algorithm also play an important role in point cloud processing. These algorithms can avoid falling into local optimal solutions and search for more global optimal solutions, thus improving the accuracy and completeness of point cloud reconstruction. By combining deep learning models and global optimization algorithms, more accurate and efficient point cloud reconstruction can be achieved, improving the quality and stability of the reconstruction results. For example, a real-time high-precision model reconstruction method based on global optimization was proposed by Xinao Xu et al. It is able to achieve higher accuracy and more stable global point cloud alignment. It is especially suitable for dynamic scenes where jitter and other factors lead to sudden changes in the velocity of the object under test [9]. Chen

Kun et al. proposed a global optimization multi-view 3D reconstruction method based on light, which is robust and can improve the accuracy and integrity of the reconstructed model [10].

4.4. Simplification and Visualization of Modeling Process through Software Packaging

Point cloud-based 3D modeling is a common method for processing three-dimensional data, and many software programs support this technique. Table 2 presents a list of some mainstream point cloud-based 3D modeling software options:

Table 2. Advantages and Disadvantages of each method

Software	Pros	Cons
Autodesk Recap	Powerful features, suitable for creating building, terrain, and infrastructure models	High price
Trimble RealWorks	Widely used in land surveying and architectural design fields	Steep learning curve
Leica Cyclone	Mainstream tool for laser scan data processing, feature-rich	Expensive
Bentley Pointools	Integration with BIM, suitable for architectural engineering	Complex usage
CloudCompare	Open-source software, comprehensive functionality, suitable for scientific research	Lack of commercial support

5. Conclusion

In summary, point cloud-based 3D modeling technology shows great potential and application prospects in reconstructing 3D models of objects and environments using data acquired by sensors such as LiDAR and cameras. This paper systematically introduces the basic principles of point cloud data processing, common methods and their key technical routes in 3D model reconstruction. By comparing the optimization-driven approaches to 3D reconstruction algorithms with interpolation or fitting strategies, we are able to better understand the limitations and challenges of the various approaches and propose potential improvements.

As the field of point cloud-based 3D modeling continues to evolve, future research will focus on overcoming current technical limitations to achieve more accurate and efficient 3D model reconstruction. By improving existing techniques, proposing innovative approaches, and enhancing computational efficiency, we are confident that we will see significant progress in the use of point cloud data for 3D modeling.

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