Research on Model Reconstruction Methods for Indoor Complex Scenes

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Abstract

With the rapid development of digital technology and urbanization, indoor 3D reconstruction plays a crucial role in the construction of smart cities. This paper proposes a multi-level point cloud modeling method for complex indoor scenes based on spatial analysis and semantic enhancement. Firstly, room-level semantic segmentation is achieved by combining legal vectors and density features; Then, the α-Shape algorithm is adopted to extract the room contour, and the corner points are identified based on the local geometric features to refine the room boundary and wall structure; Next, the wall point cloud is classified and its attributes are determined through buffer analysis and surface-plane fitting to distinguish between planar walls and curved walls. Finally, the wall line structure is optimized by using the geometric regularization strategy, and each room is integrated into a complete indoor structure model with the help of spatial topological relations.
The experimental results show that this method significantly improves the modeling accuracy and robustness in non-Manhattan structural environments, and can accurately reconstruct the geometric and semantic information of complex indoor Spaces. This provides a solid data foundation for indoor 3D reconstruction and intelligent building applications.

1. Introduction

With the rapid development of digital technology and the continuous acceleration of urbanization, the construction of smart cities has become the core direction of current urban development. In the process of building smart cities, the three-dimensional reconstruction technology of indoor space plays a key role. It not only provides high-precision data support for urban planning, architectural design and operation and maintenance management, but also creates a more intelligent, convenient and personalized living environment for residents.
Point cloud data, as a form of data with three-dimensional spatial coordinates, rich attribute information and irregular distribution characteristics, can accurately depict the complex environment in the real world and has become the most direct form of three-dimensional spatial data representation at present (Maalek et al, 2019). With its advantages in spatial perception and geometric modeling, point cloud data has received extensive attention in academic research and industrial applications, especially showing great potential in the field of indoor environment modeling.

However, in the process of constructing indoor models, the handling of complex scenes still faces many challenges (Cui et al, 2019). Its complexity is mainly reflected in the following aspects: Firstly, there are various types of indoor objects, and non-structural elements (such as tables, chairs, cabinets, etc.) increase the difficulty of reconstruction; Secondly, there are a large number of components with complex shapes and structures, such as curved walls and irregular beams and columns, etc. In addition, the diverse functions and significant material differences of the indoor space also make the modeling task more challenging.

Traditional 3D reconstruction methods usually take point cloud data as input and construct polygonal meshes in explicit or implicit ways to express the surface morphology of objects (Wei et al, 2023). However, this type of method has the following limitations when dealing with complex indoor scenes: On the one hand, the point cloud data of structural elements such as walls often deviate from the real structure due to noise, sparse sampling, occlusion and sensor errors, affecting the modeling accuracy; On the other hand, traditional methods mainly focus on the geometric level, lack understanding at the semantic level, cannot accurately obtain key parameters such as the thickness of the wall (Abadi and El-Sheimy, 2022). Furthermore, most methods rely on the Manhattan world assumption (that is, the assumption that the walls are perpendicular or parallel to each other), and have poor adaptability to the environment of non-Manhattan structures, seriously limiting their universality and application scope.

In response to the above problems, this paper proposes a point cloud modeling method for complex indoor scenes. This method first realizes the point cloud segmentation at the room level by using spatial analysis and clustering algorithms (Zou, 2023). Then, for the point cloud data within a single room, the contour extraction and feature recognition methods are adopted to accurately obtain the segmented wall information (Shen et al, 2008). On this basis, combined with geometric attributes and semantic information, the global correlation among indoor structural elements is established, and then a complete three-dimensional indoor model containing semantic labels is generated (Truong-Hong and Lindenbergh, 2022). The method proposed in this paper introduces a semantic-enhanced geometric reconstruction mechanism, which not only breaks the limitations of the traditional Manhattan hypothesis (Ning et al, 2023) and effectively adapted to the non-orthogonal structural environment, but also significantly improves the robustness of the model to noise and occlusion, thereby achieving high-precision and high-stability indoor 3D reconstruction.

2. Room Data Semantic Segmentation

This paper proposes an indoor modeling strategy that proceeds from the whole to the part and then builds the whole from the part. Specifically, the original point cloud is first divided into multiple independent indoor space units, and the wall lines are extracted based on the characteristic information of the point cloud of each room. Then, they are connected according to the spatial topological relationship between the rooms, thereby reconstructing the complete indoor structure model.

This section focuses on introducing the room semantic segmentation method of point clouds (Kolodiazhnyi et al, 2023). By using the ceiling point clouds classified by semantics for room point cloud segmentation, the aim is to achieve a reasonable division from the whole to the part, so as to reduce the influence of cross-room interference on the modeling accuracy and effectively reduce the complexity of overall point cloud processing. The specific methods include: First, extracting the ceiling point cloud through the normal vector analysis combined with the pixel density segmentation method; Then apply the clustering algorithm to identify the clustering areas of each room; Finally, the precise segmentation of the room boundaries is further completed through contour extraction.

2.1 Voxel Density Segmentation Based on Normal Direction Judgment

In the process of indoor 3D reconstruction, room segmentation is a key prerequisite step. Its main purpose is to reduce the mutual interference between point clouds of different rooms, thereby improving the accuracy of the overall modeling and achieving the modeling strategy from the whole to the part. This paper proposes a point cloud slicing method combining the vector and the Z-axis density gradient for accurately separating the ceiling point cloud. Firstly, based on the histogram of point cloud density in the Z-axis direction, identify the point cloud area with prominent density located above the scene, which usually corresponds to the ceiling surface. Considering that the ceiling is usually one of the largest and smoothest horizontal planes in the indoor space, it has a relatively high point cloud density distribution in the Z-axis direction. To further eliminate the vertical structural elements such as walls and columns mixed in the upper point cloud, this paper introduces the normal vector feature for auxiliary judgment. Let the Z-axis component of the point cloud normal vector be N_z and the voxel density gradient be D. Perform voxel division on the Z-axis in units of 0.3m. On this basis, a judgment threshold is set: When $N_z>0.9$ and $D>0.25$, it is determined that this point belongs to the ceiling area. By combining the geometric directionality and density distribution information, this method can effectively identify the ceiling point cloud and simultaneously eliminate the vertical structure interference points, thereby providing an accurate data basis for subsequent room clustering and modeling. The segmentation effect is shown in Figure 1 below.

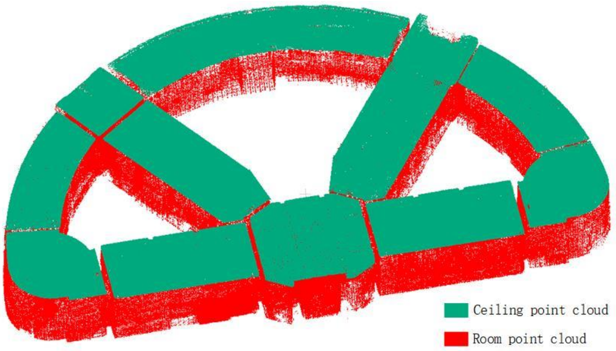

Figure 1. Point cloud semantic segmentation result.

2.2 Point Cloud Clustering Based on Adaptive Density Estimation

In complex indoor scenes, rooms are often interconnected through structures such as doors, Windows, and corridors. Spatial clustering of the original point cloud directly is prone to misclustering due to these connecting structures. To improve the accuracy and robustness of room division, this paper proposes a point cloud clustering method based on adaptive density estimation. This method is Based on the DBSCAN (density-based Spatial Clustering of Applications with Noise) algorithm accelerated by Kd-Tree and introduces a local Density adaptive mechanism. Enhance the adaptability to non-uniform density and scale variations.

In this study, an efficient neighborhood search structure is constructed, and the neighborhood point distribution of each point under different radii is statistically analyzed to estimate the local density level (Mo et al, 2024). Based on the density gradient change and the prior of the wall structure (such as a wall thickness of approximately 8-12 cm), dynamically adjust the neighborhood search radius of each point to 8 cm and the minimum number of neighborhood points to 25 to avoid overly rough clustering boundaries or misjudgment caused by fixed parameter Settings. The neighborhood judgment is as follows:

$$N_r(p_i) = \{p_j \in P| \ \ \| p_j - p_i \| \le r\} \tag{1}$$

$$\rho(p_i) = \frac{1}{n}\sum_{k=1}^{n} \left| N_{r_k}(p_i) \right| \tag{2}$$

where $N_r(p_i)$ = Point neighborhood
P = Point aggregation
$\|p_j - p_i\|$ = Euclidean distance between points
r = Neighborhood radius parameter

The clustering process adopts a bottom-up density expansion strategy: Starting from the seed point, if its local density exceeds the threshold, it expands into a new clustering cluster and recursively expands the density reachable points within its neighborhood. Finally, the ceiling point cloud is divided into multiple room point cloud clusters with interconnected spatial densities and adaptively adjusted boundaries.

Furthermore, to further enhance the geometric consistency of the clustering results, this paper introduces spatial regularity constraints and geometric consistency optimization mechanisms on the basis of the initial clustering to ensure that the final room clustering has clear spatial boundaries and topological independence.

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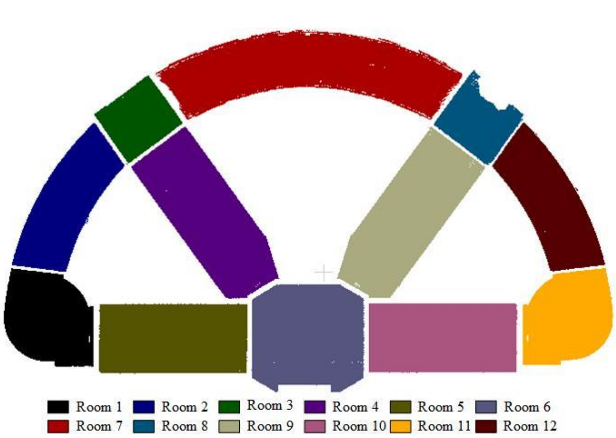

Figure 2. Ceiling point cloud clustering.

Different from the traditional DBSCAN algorithm, the method proposed in this paper significantly enhances the perception ability of point cloud density changes, can effectively adapt to structural changes such as wall connection areas and door openings, and improves the purity and stability of spatial division.

2.3 Voxel Density Segmentation Based on Normal Direction Judgment

To achieve further precise division of the indoor spatial structure from the ceiling clustering results, this paper performs contour extraction operations on each clustering unit (room ceiling point cloud) to obtain the boundary information of the room and complete the spatial division of the original point cloud accordingly.

Considering the complexity of the indoor space structure, actual rooms often have irregular geometric features such as local depressions and protrusions, and the traditional convex hull method is difficult to accurately depict their true boundaries (Wang et al, 2024). To this end, in this paper, the α-Shape algorithm based on triangulation is adopted to extract the two-dimensional boundary contour of the ceiling point cloud. This algorithm can achieve adjustable geometric approximation ability between the convex hull and the fine boundary, and can better reveal the detailed features such as the concave corners and turns of the wall, thereby generating a contour description that is more in line with the actual room structure, as follows specifically:

$$S = \{\mathbf{s}_i = (x_i, y_i)\}_{i=1}^{N}, \quad C_\alpha = \partial K_\alpha(S) \tag{3}$$

where $S \in R_2$ = The two-dimensional point set formed by point cloud projection
$K_\alpha(S)$= α - complex constructed based on α radius
∂K_α = Boundary of the α - complex

The point cloud of each ceiling cluster is projected onto the xy plane to construct a two-dimensional point set. Subsequently, the contour of the projected point set is extracted through the α-Shape algorithm to obtain the two-dimensional boundary polygon of each room. The contours extracted from each room are shown in Figure 3 below. (Room 13 has missing point clouds and ceiling point clouds in the original point cloud. Therefore, Room 13 is intervened by using layering processing to extract the contours from the layering point clouds.)

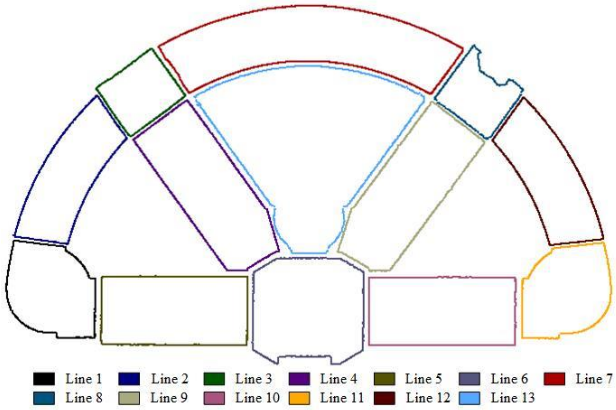

Figure 3. Room outline.

3. Room Structure Construction and Topology

Based on the results of room segmentation, this section extracts the information of wall lines and combines the spatial topological relationship to construct an overall indoor model, achieving the modeling goal from the local to the whole. Method: First, identify the corner points of the room contour, divide it by wall sections, and determine the wall type in combination with the corresponding wall point cloud to distinguish between flat walls and curved walls, and at the same time, the body wall section information; Subsequently, the wall lines are regularized according to the wall section information, and based on the topological connection relationship between rooms, they are integrated into a complete indoor structural model.

3.1 Contour Corner Point Extraction Based on Local Geometric Features

In indoor Spaces with complex or irregular shapes, directly extracting wall lines from wall point clouds often faces interferences such as structural discontinuity and furniture occlusion. To enhance the robustness of structural recognition, this paper starts from the extracted room contour points and realizes the structured expression of the room contour through corner point recognition (Lu et al, 2014). Taking the single contour point as the center, its local neighborhood is constructed. The covariance matrix is calculated based on the neighborhood points, and feature analysis is conducted on it to determine the characteristic attributes corresponding to its primary and secondary directions. If the eigenvalues in the main direction are significantly greater than those in the secondary direction, it indicates that the point cloud distribution shows a linear extension trend, and this point is determined as a non-corner point. If the two are similar, it indicates that there are turning or scattered features in the local structure, and this point is marked as a corner point, as follows:

$$C_i = \frac{1}{|N_i|} \sum_{p_j \in N_i} (p_j - \overline{p}_i)(p_j - \overline{p}_i)^T \tag{4}$$

where N_i = Neighborhood set of point P_i
P_i = Centroid within the neighborhood
C_i = Point P of covariance matrix

This method can effectively identify structural change points such as folding angles and bends in the contour, thereby reasonably segmenting the contour curve and extracting wall sections that are structurally independent and continuous. Compared with the strategies based only on global curvature or Angle changes, this method has stronger robustness when dealing with actual interior contours with noise or slight bends, providing a geometric basis for subsequent wall type recognition and structural modeling.

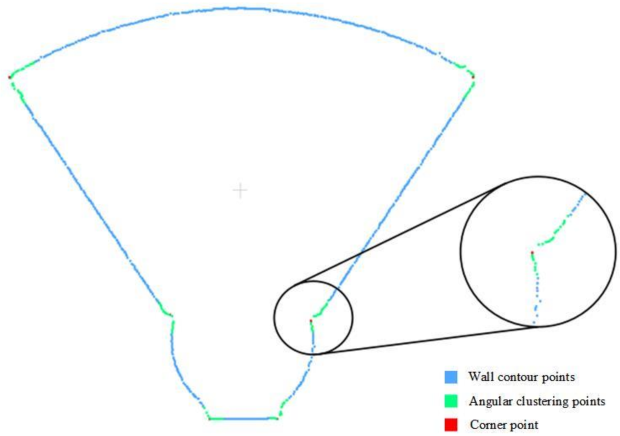

Figure 4. Corner point recognition.

3.2 Buffer Zone Analysis and Fitting Discrimination

To extract the wall point clouds corresponding to each wall segment and identify their attributes, this paper first constructs a buffer based on the contour line segments. The specific approach is: Extend a fixed width along the contour of each wall section to both sides in the normal direction (equivalent to the thickness of the wall) to form a local buffer zone. Then, combined with the point cloud data in the room, the point clouds falling in the buffer zone are screened out as the candidate wall point clouds for this wall section. This operation effectively eliminates the interference of non-structural elements such as columns and furniture near the wall on the modeling, and improves the purity of wall extraction.

After extracting the point cloud of the wall section, it is necessary to further identify its geometric attributes to determine the type of the wall (Geng et al, 2024). To this end, this paper constructs a structural classification framework based on contour-point cloud collaborative discrimination, comprehensively considering the geometric fitting residuals and curvature evolution characteristics. Firstly, for each section of the wall contour line, least squares quadratic curve fitting is carried out to extract the high-order coefficient A, which is used to preliminarily determine whether the wall has a nonlinear trend. Subsequently, the point clouds of the corresponding wall sections were respectively fitted into planar and arc-shaped models, and the support rates of the point clouds under their respective fitting residuals were calculated. Through linear analysis and model comparison, the categories of each section of the wall were finally classified to obtain the corresponding wall point clouds, as shown in Figure 5 below:

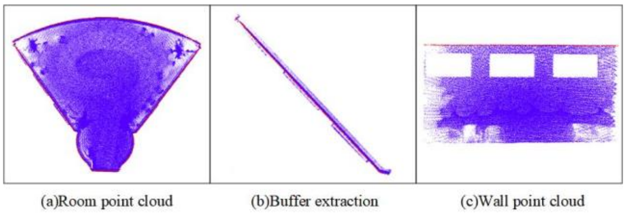

Figure 5. Wall buffer zone treatment.

Subsequently, the point cloud of the wall is processed and its structural attributes, fitting parameters and other information are recorded, which are used as the structural input for subsequent structural regularization and topological construction.

3.3 Wall Regularity and Spatial Topology Construction

During the process of extracting wall segments, limited by factors such as point cloud occlusion, absence or buffer overlap, the extracted wall lines often have geometric inconsistency problems such as position offset and length error. To improve the modeling accuracy, this paper introduces the geometric regularization strategy to optimize and adjust the initial wall line segments. Specifically, it includes: imposing parallelism constraints on the direction of the wall lines, performing boundary pruning on the length, and alignment correction on the endpoints, so as to make the extraction results more in line with the actual spatial structure. The specific effect is shown in the following figure 6:

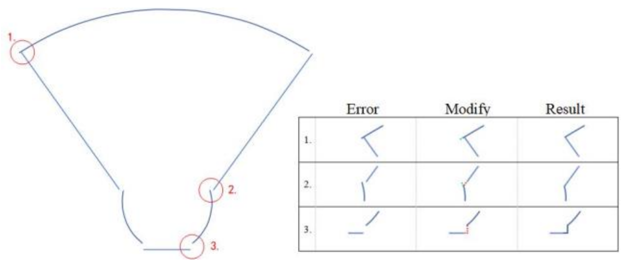

Figure 6. Regularized correction.

After obtaining the regularized wall lines of each room, the spatial topological relationships between rooms are further established. Specifically, this study analyzes the geometric alignment, spatial overlap ratio, and normal vector consistency between adjacent room walls to identify whether the wall segments exhibit one-to-one or one-to-many sharing relationships. The topological effect is shown in the following figure 7.

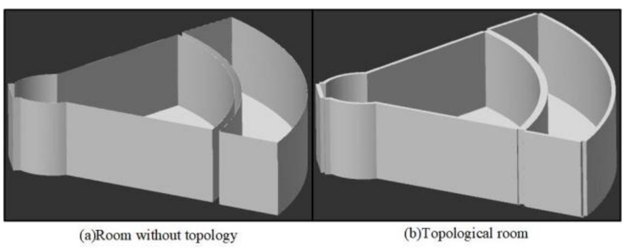

Figure 7. Wall topology.

Based on these relationships, a global wall mapping table is constructed to generate a comprehensive topological graph of the indoor space, enabling the integration of individual room models into a unified structural model. This topological structure not only enhances the consistency and completeness of multi-room modeling but also provides a precise and high-quality geometric foundation for advanced applications such as indoor scene reconstruction and BIM modeling.

4. Experimental Process

4.1 Experimental Data

In this study, three datasets are used for experiments. Dataset a is the publicly available S1 dataset, which includes an L-shaped corridor and three rooms, with a total of 442,506 points. Datasets b and c are both sourced from the public benchmark datasets provided by ISPRS. Point cloud dataset b was captured by sensors in Building B of the Faculty of Engineering at the University of Melbourne, Australia. It contains a long corridor, six rooms, and walls of varying thicknesses, comprising 414,821 points. Dataset c corresponds to the Granger Museum, containing 13 rooms with varying wall thicknesses and a total of 45,176,594 points. The experimental data is illustrated in the figure 8 below.

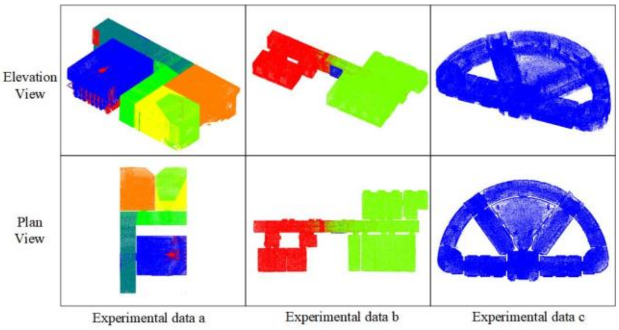

Figure 8. Original point cloud data.

4.2 Buffer Zone Analysis and Fitting Discrimination

Figure 9 illustrates the reconstruction results of the proposed method across three different datasets. The results demonstrate that the proposed algorithm can accurately identify the spatial extent of wall segments, extract wall thickness, and perform component-based 3D modeling of walls. It effectively distinguishes between typical structures such as corridors and rooms, as well as non-Manhattan elements like oblique and curved walls.

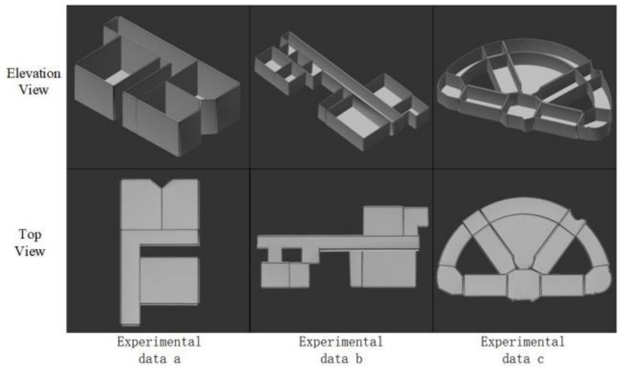

Figure 9. Model result.

The reconstructed room models not only reflect realistic wall thickness, but also assign default values for walls with missing thickness information. The method shows strong adaptability in recognizing non-axis-aligned structures (e.g., slanted or curved walls). Furthermore, the proposed approach exhibits robustness when processing noisy and cluttered point cloud data, enabling stable and precise structural extraction and modeling.

4.3 Experimental Analysis

The volumetric modeling algorithm proposed in this study offers distinct advantages over existing methods through a "global-to-local and local-to-global" strategy. The algorithm begins by analyzing the global room structure and then focuses on the geometric and topological details of local wall segments. Through processes such as contour extraction and wall attribute recognition, high-precision modeling is achieved. Subsequently, the spatial topological relationships between rooms are constructed while preserving local structural details. This approach ensures both the accuracy of local room components and the coherence of the overall spatial structure.

Moreover, the proposed algorithm does not rely on the Manhattan-world assumption, making it well-suited for indoor point clouds containing non-orthogonal structures such as oblique and curved walls. By incorporating multiple constraints—including spatial topology, geometric consistency, and feature awareness—the method demonstrates strong robustness and generalization ability. It can effectively reconstruct complex indoor environments, yielding semantically structured 3D models with wall thickness and geometric attributes.

To evaluate the accuracy and effectiveness of the algorithm, a reference model R and a source model S are constructed. Based on previous studies, three commonly used evaluation metrics—completeness, correctness, and accuracy—are adopted for comprehensive assessment (Tran et al, 2019). The calculation formulas for these metrics are given as follows:

$$M_{comp}(S,R,b) = \frac{\sum_{j=1}^{n} \left| \bigcup_{i=1}^{m} \left(\zeta(S^i) \cap b(R^j) \right) \right|}{\sum_{j=1}^{n} \left| R^j \right|} \tag{5}$$

$$M_{corr}(S,R,b) = \frac{\sum_{j=1}^{n}\left|\bigcup_{i=1}^{m}\left(\zeta(S^i)\cap b(R^j)\right)\right|}{\sum_{j=1}^{m}\left|S^i\right|} \tag{6}$$

$$M_{acc}(S,R,r) = \mathrm{Med}(\pi_j^T p_i), \quad \text{if } |\pi_j^T p_i| < r \tag{7}$$

The precision effect is shown in the following table 1:

Data number	M_{Comp}	M_{Coor}	M_{Acc}/cm
a	0.95	0.93	2.458
b	0.91	0.89	3.521
c	0.82	0.78	9.673

Table 1. Accuracy Sandard

Although the proposed modeling method demonstrates promising performance in recognizing both global and local indoor structures, certain limitations remain during the actual reconstruction process, as illustrated in Figure 10. First, in areas with severe point cloud incompleteness, the extracted contour points may deviate significantly from the true wall boundaries, leading to inaccuracies in corner detection and wall fitting. This ultimately affects the overall reconstruction quality of the model, as shown in Figure 10(b). Moreover, when dealing with large-scale indoor point clouds, concave or geometrically complex corner regions may be overlooked or oversimplified during regularization or surface fitting, as shown in Figure 10(c), resulting in geometric discrepancies between the reconstructed model and the real scene. These issues reduce the accuracy of the model in representing fine-scale structural details.

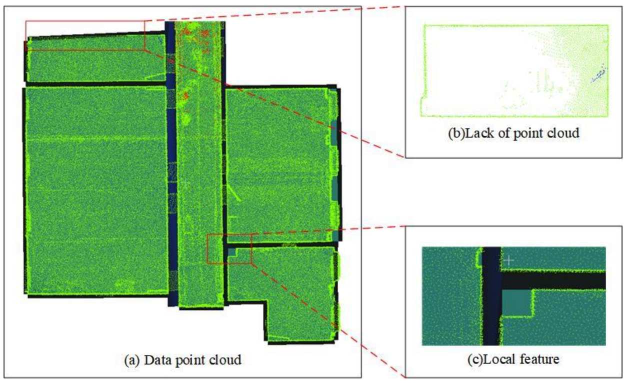

Figure 10. Local problem.

To further improve the precision and robustness of the model, future work will focus on refining the algorithm. On one hand, more robust feature extraction and fitting techniques will be introduced to enhance the recognition of local structures. On the other hand, the integration of semantic information and multi-scale geometric constraints will be explored to achieve more accurate boundary recovery and component-level detail modeling, thereby improving the overall reconstruction quality and adaptability of the approach.

5. Conclusion

This paper presents a robust volumetric modeling method for tackling the challenges of wall structure recognition and reconstruction in complex indoor environments. The proposed approach encompasses key stages including room segmentation, contour extraction, wall identification, and spatial topology construction. By integrating local geometric feature analysis, curvature evolution assessment, and topological consistency constraints, the method operates independently of the Manhattan world assumption and effectively handles non-orthogonal indoor structures such as slanted and curved walls. It enables component-level wall modeling with realistic thickness attributes. Experimental validation on multiple public and real-world datasets demonstrates the method’s strong adaptability and robustness in room segmentation, wall type recognition, and accurate 3D reconstruction. Nonetheless, the method may face limitations in cases of sparse point clouds, significant structural occlusions, or fine-scale complex elements, potentially affecting modeling completeness and precision. Future work will focus on enhancing the recognition and fitting of structural details by incorporating multi-source semantic information and time-series point clouds. Furthermore, the framework will be extended with multi-scale geometric constraints to support high-precision modeling in dynamic environments and facilitate integration with BIM systems, thereby providing a more reliable foundation for applications such as digital twins, indoor navigation, and spatial intelligence analysis.

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