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Parametric modeling of walls based on voxels of slices and line segment detection

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Abstract: Building Information Model (BIM) is increasingly being used in the research of construction. The demand for low-cost and efficient access to architectural models is also on the rise. However, generating a parametric model from a point cloud will face interference from other facilities and will be affected by the quality of the measured point cloud. This paper describes a method for generating parametric models from laser-scanned point clouds. With slice voxel selection and line segment detection, the structural framework of the walls can be quickly extracted. By reducing the impact of missing furniture and data on the room, the new approach is applicable to most raw point clouds. This method has potential in multiple directions such as rapid BIM modeling, large-scale room reconstruction, and robot spatial perception.

Key words: point cloud, model reconstruction, voxels, line detection

1. INTRODUCTION

With the development of the construction industry, the demand for building information models (BIM) is increasing. BIM is widely recognized and used among researchers, policymakers, and construction practitioners [1]. Obtaining high-precision BIM models rapidly is very helpful to improve the efficiency of engineering and research. On the other hand, BIM may face different compatibility and information loss when transferring between different software [2]. Therefore, it is important to develop automated methods suitable for BIM parametric modeling. Researchers have tried to build information models from 3D point clouds, which describe the coordinates of building components [3,4]. However, there are still challenges caused by noise and information loss in semantic generation for large spaces [5].

This study proposes a parametric model reconstruction method for walls, which is simple and fast while reducing noise interference. This method eliminates possible noise by converting the point cloud slice projection into voxels. Then, the original line segment set is obtained by the method of line segment detection and regularization. Finally, the center line of the wall can be determined by planar segmentation. The wall centerline obtained by this method will be represented as an acceptable parameter for the BIM model. This method has the potential to be extended to more complex and larger buildings.

2. BACKGROUND

Point cloud data has high accuracy and density, and is widely used in a variety of occasions [6]. Model reconstruction of point clouds is also a valuable research direction. In the field of architecture, it covers the reconstruction of 3D models and 2D drawings. This section reviews some of the existing studies.

2.1. Point cloud and BIM

BIM reconstruction with scan data from buildings is called scan-to-BIM, which has received more and more attention in recent years [7]. Liu et al. [8] used Dynamo to automate the process of generating steel models from laser scan data. Wang et al. [9] reconstructed mechanical, electrical, and plumbing (MEP) systems in BIM models from 3D scan data. Adán et al. [10] comprehensively considered the 3D coordinates and RGB colors of the point cloud to fully automatically identify the “secondary” building components attached to the wall. It can be seen from the above research that point clouds have a variety of functions in the construction industry. One of the keys to the application of point clouds in BIM is to obtain the semantic information of the model by using the location, color or other characteristics of the points.

The ultimate goal of scan-to-BIM is to generate reliable BIM models [11]. The development of reconstruction techniques is one of the research hotspots.

2.1. Reconstruction from point cloud

There are many approaches to getting the model from point clouds. The RANSAC-based fitting algorithm can extract the plane in the point cloud, so it has been adopted by many researchers [12,13]. The method of spatial segmentation can make the results of the reconstruction more robust [14]. Fang et al. [15] solved the Markov random field problem to draw the boundaries of the different spatial partitions within the building. In addition, some researchers have defined the design grammar of structures. Ochmann et al. [16] extracted the wall planes in the point cloud and assembled the walls by defining the connections of the corners. Kim et al. [17] used pixels to represent the cross-section of the point cloud, getting the architectural drawings by specifying the extension of the straight line. Deep learning can also assist in reconstruction. Semantic segmentation neural networks (e.g., Pointnet [18], RandLA-Net [19], MeiEA-Net [20]) can be used to obtain smaller building components. Line detection represented by the Hough transform is also used in the field of reconstruction. Bosché et al. [4] integrated BIM with Hough curve detection to scan cylindrical components.

However, there are drawbacks to the current approach. Planar fitting is sensitive to point cloud quality and identifies nonsensical planes, often requiring additional strict constraints. Most of the predefined rules are represented by mathematical formulas, and their generalization in different classes of buildings may require further validation. Deep learning methods are highly accurate but require large datasets and long training periods, which makes them difficult to be widely used in practice. Line detection has good versatility and fast speed, but it is more affected by furniture than plane detection. Therefore, it makes sense to propose a simpler model reconstruction method with competitive results.

3. METHOD

3.1. Voxels of point cloud slices

Each point in the original point cloud data is represented as a three-dimensional coordinate (xyz) in absolute space. The first step in data processing is to obtain an equidistant slice of the original point cloud based on the z-coordinates. The more the number of slices, the larger the range of adjustments for the reconstruction results. Depending on the accuracy of the scanning device, the overall point cloud may be slightly tilted in the horizontal plane. Therefore, this study selected slices in the 0.1 to 0.9 range of heights and divided the point cloud into exactly 8 slices.

Next, filter the noise based on the number of voxels. Voxels can be simply understood as the three-dimensional form of pixels. Since the voxels formed by points on the same plane do not overlap, the area of the surface can be represented by the number of voxels. In this case, the number of voxels in slices with a large amount of furniture will increase significantly. The furniture in the room is distributed on the lower half of the room, so 4 (or less) of 8 pieces can be selected as the final slice. Finally, the selected slices are projected onto the same plane as binary images for line detection. The workflow of this process is shown in Figure 1.

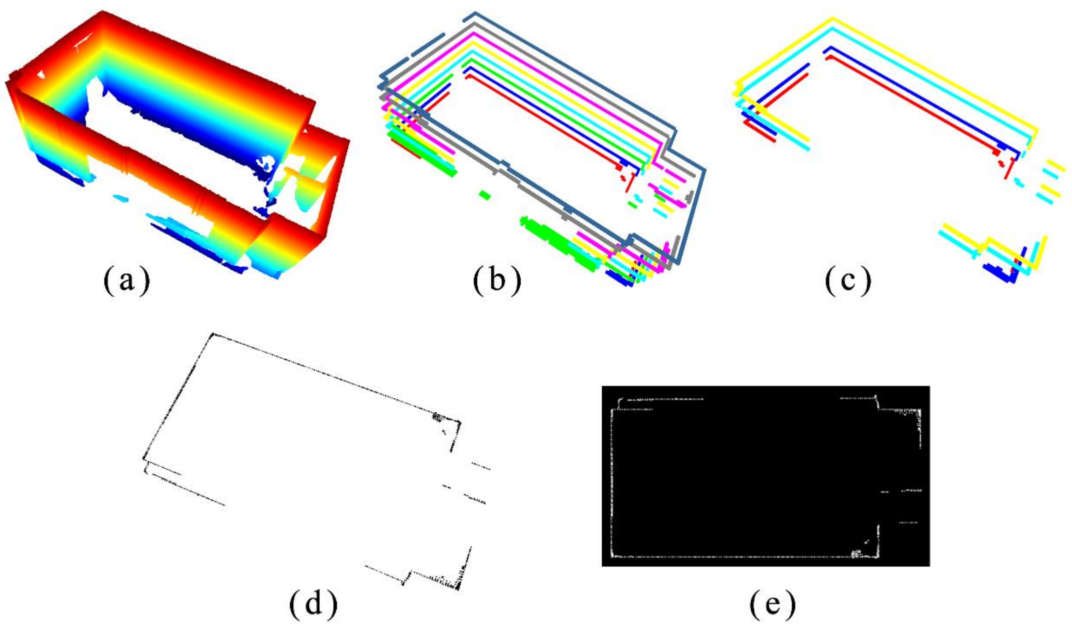


Figure 1. From point cloud to binary image

Since voxels have a certain side length and volume, there is definitely a loss of information in the process of representing points as voxels. Therefore, the size of the voxels depends on the error that can be accepted in actual use.

3.2. Line segment detection

Line detection includes fully automated pixel-based detection (e.g., Hough Transform [21], EDlines [22]) and deep learning-based detection (e.g., HAWP [23]). The simple line segment extraction lags behind the existing methods in the accuracy of model reconstruction. However, through reasonable regularization, the original line segment set of the building plane can be quickly obtained without prior knowledge parameters.

Among them, the probabilistic Hough transform (HoughP) is a method that has been widely used for a long time. The Hough transform takes advantage of the one-to-one correspondence between the image space and the parameter space. Points in image space can be represented as straight lines in parameter space. If some points are colinear in image space, they have the same intersection point in the line in parameter space. Similarly, if the number of straight lines intersecting at the same point in the parameter space is greater than a threshold, a straight line is considered to exist in the image space. However, the polar coordinate system is usually used instead of the Cartesian coordinate system. The basic formulas are as follows.

$$y = -\frac{\cos\theta}{\sin\theta}x + \frac{r}{\sin\theta} \tag{1}$$

$$r = x\cos\theta + y\sin\theta \tag{2}$$

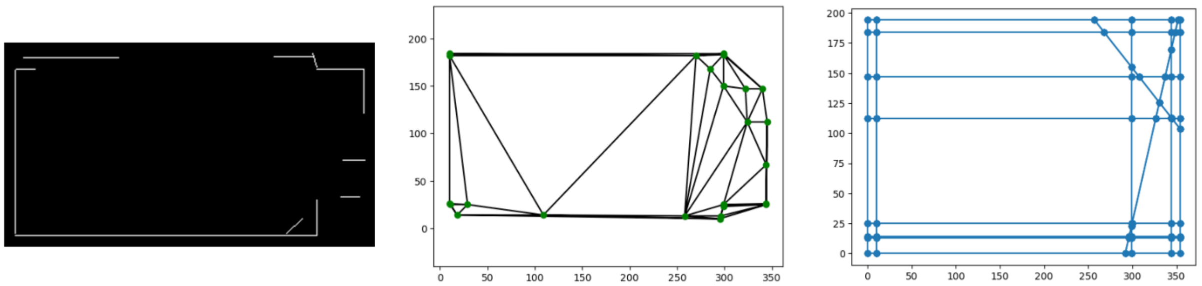
It is important to note that deep learning-based methods tend to have better results than morphological methods. However, in practice, there is often no complete dataset for training. Therefore, these methods are not recommended.

3.3. Planar segmentation

Before plane splitting, the line segments should first be regularized, which includes the merging and correction of some line segments. There are two parameters in this process, which are distance and angle. Segments that exceed the threshold will be merged or horizontal. The study discusses two methods of plane segmentation, including mesh-based segmentation and lines arrangement segmentation.

Meshes play an important role in numerical calculations and are often used in numerical simulations such as finite elements. Meshes are divided into various types based on morphology, such as triangles , quadrilaterals, tetrahedrons, and pyramids. In this study, two-dimensional triangular meshes are selected to maximize the use of nodes to form more possible edges. Meshes can be obtained by the Delaunay triangulation algorithm, in which the circumscribed circle of each triangle dosen't contain other vertices. The Delaunay triangulation results are unique, so the reconstruction model of the same original point cloud is stable.

lines arrangement segmentation refers to the division of the plane by extended line segments. The advantage of this method is that it can make full use of the original line segment set, so that the reconstruction results are more reasonable. At the same time, by extending the line segments to make them intersect each other, the non-closed loops can be regularized to obtain watertight boundaries. These two methods are shown in Figure 2.



Line segments   Mesh-based segmentation   Lines arrangement segmentation

Figure 2. Split the projection plane

The final boundary is determined by comparing the original point cloud projections. When the overlapping area of the plane and the projection accounts for more than 50% to 70%, the plane will be retained. Segments that occur only once are considered as room boundaries.

4. EXPERIMENT

In the validation experiment, Open3d was chosen as the point cloud processing tool and selected HoughP as the line detection kernal [24]. Experimental samples contain separate rooms in both public and local sampled datasets. Their morphology and characteristics are shown in Figure 3 and Table 1 (Characteristics are categorized according to whether they exist). Prior to the test, all samples were simply filtered to remove a small number of significant outliers and increase the speed of the experiment.

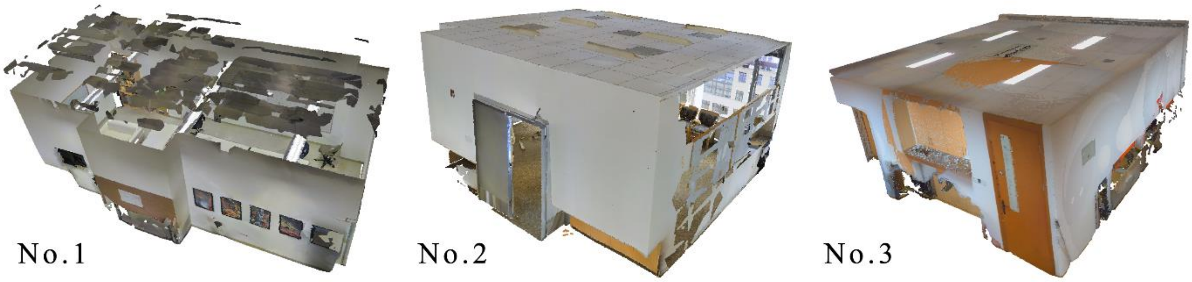


Figure 3. Appearance of samples

Table 1. Characteristics of samples

No.	Dataset	Characteristics: Not smooth	Inclined walls	Lots of furniture	Incomplete	Tiny walls
1	S3DIS	No	No	No	No	Yes
2	S3DIS	No	No	Yes	Yes	Yes
3	Ours	Yes	Yes	Yes	Yes	No

This study records the results for each process, as shown in Figure4 (Part 1: Voxels of point cloud slices, Part 2: Line segment detection, Part 3: Mesh-based segmentation, Part 4: Lines arrangement segmentation). It can be seen that the screening of the slices filtered most of the furniture. However, there is still residual noise, especially on bookshelves close to the walls. Point clouds of debris close to the wall can destroy the outer edge of the reconstruction. A mutilated point cloud interferes with the original segment collection.

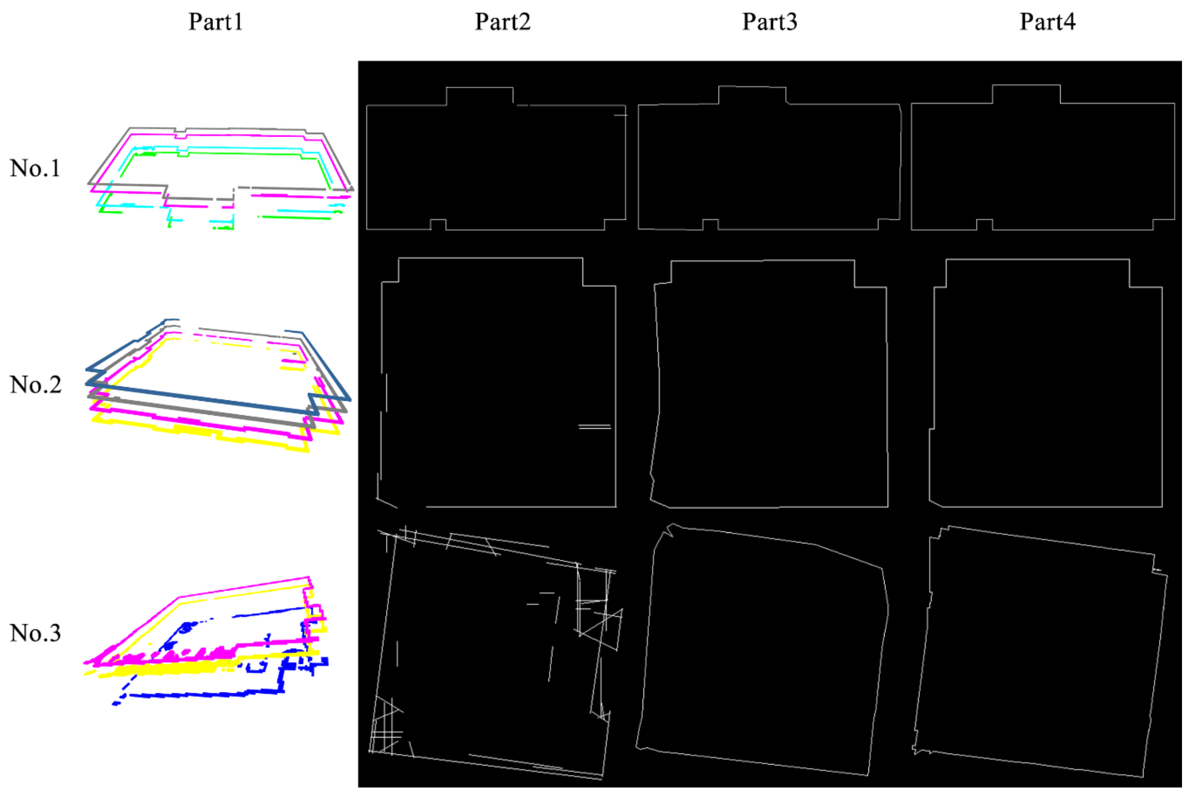


Figure 4. Intermediate results

The format of the BIM wall parametric modeling is shown in below. In order to prevent errors caused by line segments that were too short, unqualified segments were removed.

$$Create(Document, IList(Curve), WallTypeId, LevelId, Boolean) \quad (3)$$

The 3D and top views of the BIM model are shown in Figure 5. According to the model, the results demonstrate overall accuracy. The plane division method based on spatial segmentation performed better than the grid-based method, because the latter only used the position of the endpoints. As a result, mesh-based segmentation was no longer used in this study.

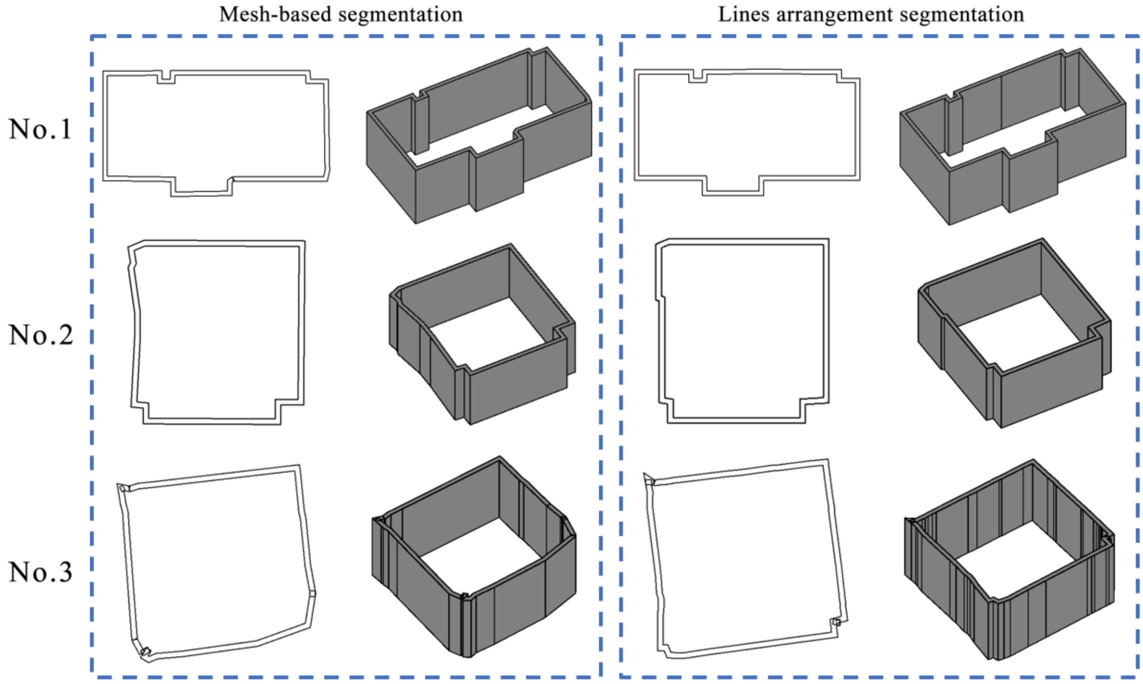


Figure 5. Reconstructed BIM model

In addition, this study preliminarily examined the results of the new method in the reconstruction of complex building structures. The result is shown in Figure 6. It can be observed that this method can determine the general shape of the building. However, the model cannot be properly reconstructed in many details. Therefore, it is necessary to filter out useless segments before plane splitting. Moreover, a large number of tiny planes will cut the line into many segments, so it is better to regularize the final set of line segments.

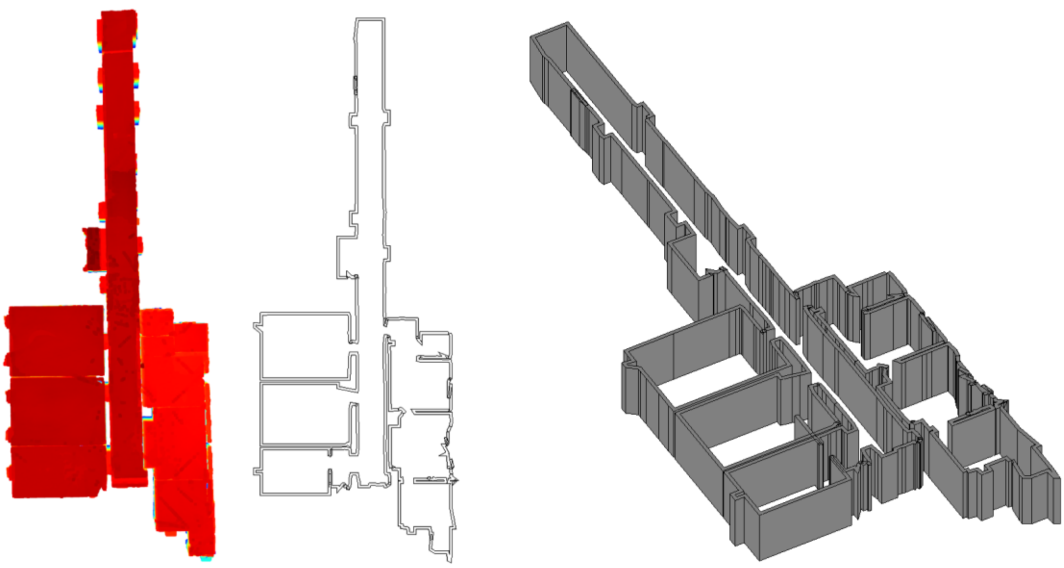


Figure 6. Complex structure model

5. DISCUSSION

This study proposed a simple parametric modeling method, which can quickly and robustly extract the BIM model of the wall from the point cloud. The new method has advantages in the number of parameters and the interpretability of parameters and can be flexibly applied in different situations. In addition, the method has good robustness and can be applied to non-Manhattan spaces. It also proves the high upper bound of the line segment detection technique such as Hough transform in parametric modeling, where the original line segment set is obtained directly from the point cloud projection. The method has been successful in the reconstruction of a single room from a public dataset and a self-built dataset. Most importantly, this method has few prior parameters based on specific buildings, which makes the cost of using it significantly lower than some higher-precision methods. In the future, we will develop methods that can be used in large-scale rooms, which are related to the detection of spatial location and the handling of more impurities.

Currently, there are some limitations to this method. First, while segment detection avoids the problem of plane detection generating a large number of useless planes, it is still affected by debris. Segment detection ignores building height information, which reduces the required parameters but runs the risk of over-detection. The disorganized results severely affect the speed of parameter generation, and make the centerline of the model wall jagged. Second, although the method can obtain most of the walls in the point cloud, there are defects in some special rooms. For example, curved wall reconstruction is a common difficulty for existing methods, in which Hough line segment detection also performs poorly. More sophisticated line detection techniques should be tried, and the curve can be fitted with short straight lines. Third, a high-precision analysis method is needed. Although the results of the new method demonstrate visual acceptability, it is necessary to quantitatively represent the morphological gap between the BIM model and the original point cloud.

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