FROM BIM TO POINTCLOUD: AUTOMATIC GENERATION OF LABELED INDOOR POINTCLOUD

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ABSTRACT:
With the development of deep learning technology, a large number of indoor spatial applications, such as robotics and indoor navigation, have raised higher data requirements for indoor semantic model. However, creating deep learning classifiers requires a large number of labeled datasets, and the collection of such datasets requires a lot of manually labeling proces, which is labor-intensive and time-consuming. In this paper, we propose a method to automatically create 3D point clouds datasets with indoor semantic labels based on parametric BIM model. First, a automatic BIM generation method is proposed through simulating the structure of interior space Secondly, we use a viewpoint-guided labeled point cloud generation method to generate synthetic 3D point clouds with different labels, color information. Especially, noise are also simulated with a gaussian model. As shown in the experiments, the point cloud data with labels can be quickly obtained from existing BIM models, which will largely reduce the complexity of data labeling and improve efficiency. These simulated data can be used in the deep learning training process and improve the semantic segmentation accuracy.

1. INTRODUCTION

1.1 General Instructions

With the development of artificial intelligence and deep learning, deep learning has become one of the mainstream methods for semantic segmentation of 3D point clouds. However, creating deep learning classifiers requires a large number of labeled datasets, and the research community engaged in 3D semantic segmentation generally lacks labeled datasets(Gao et al., 2020), and the production process of such datasets requires manual data collection and manual semantic segmentation, which is labor-intensive and time-consuming. Fortunately, building information modeling (BIM) has been widely used in the architecture, engineering, construction, and facility operations (AECO) industry in recent years due to its improved productivity, efficiency, and quality of construction projects(Migilinskas et al., 2013). Many organizations around the world have adopted BIM in their projects (Azhar, 2011) and generated a large collection of 3D BIMs (Khosrowshahi and Arayici, 2012). Since as-built building information models (BIMs) are a semantically rich form of facility information, the need for specialized annotation work can be effectively circumvented in the construction industry by transferring semantic information from these BIM models into point clouds to generate synthetic datasets that can somewhat replace real datasets.

As a result, a great deal of research on synthetic datasets has been conducted by many scholars within the field of computer vision. Datasets generated from virtual environments can provide an almost unlimited number of diverse datasets, greater flexibility, and lower creation costs. Additionally, synthetic data can theoretically be an effective substitute for real-world data in cases where it is difficult to obtain ground truth information. Therefore, many researchers have investigated the use of synthetic datasets in several domains, including medical imaging(Itu et al., 2018), target detection(Pepik et al., 2012), semantic segmentation(Ros et al., 2016), and autonomous driving(Pan et al., 2017).

As point clouds generated by laser scanning and photogrammetry are composed of points captured from the surface of a 3D object, we are able to generate data by a variety of different means, including random distribution of points on the surface of the object (Ma et al. 2020) and adding random noise to each point (Schnabel et al., 2007). Some scholars have used depth-based semantic per-pixel tagging as an indoor scene understanding problem and demonstrated the potential of generating an almost infinite amount of tagged data from synthetic 3D scenes to train deep learning methods(Handa et al., 2016). Researchers generated synthetic datasets by using OpenGL to place virtual cameras in a 3DCAD model. In the process, they simulated sensor noise in Kinect to generate a more realistic set of synthetic data and obtained comparable results on the real-world dataset. In addition, video game scenes can be captured (Yue et al., 2018), which can be used to generate point clouds by BIM models and used as training datasets. These synthetic data as a complement to real-world point clouds resulted in a 7.1% increase in IoU (intersection over union) (Ma et al., 2020). According to researchers using commercial BIM software, a detailed step-by-step procedure was developed for converting 3D models to point clouds (Jong et al., 2020). However, the step required a great deal of labor for model processing using three commercial software programs, and the generated point cloud models did not consider occlusion relationships, point cloud noise, and color information. The relationship between objects in a scene has been studied. For instance, the HPR algorithm (Hidden Point Removal) offers an initial approximation of the visibility of a point cloud based on a given viewpoint without the need for surface reconstruction or normal estimation (Katz et al., 2007).

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Labeled point clouds generated by laser scanning simulation tools from the geosciences can take into account occlusion relationships and simulated noise in the scene (Noichl et al., 2021), but lack consideration of object component types, the noise estimates of point clouds are inadequate, and the process requires a degree of labor cost.

Many scholarly studies have demonstrated the effectiveness of synthetic datasets, where the acquisition of data using traditional remote sensing methods requires a substantial time and effort investment, and manual acquisition of data is accompanied by limited data diversity and quantity. Furthermore, some problems such as a low level of automation, an insufficient consideration for scene occlusion relationships, and a lack of consideration for sensor measurement errors and object material types exist in the methods of generating synthetic datasets using 3D models.

In order to address the appeal issues, our research demonstrates how to quickly and automatically create 3D point cloud datasets with indoor semantic labels based on BIM models using the HPR algorithm, thereby providing more indoor 3D training data required for 3D point cloud semantic segmentation by deep neural networks. This will simplify acquiring labeled 3D point cloud data, reduce human and material resources, and enhance the accuracy of 3D point cloud segmentation networks.

2. METHOD

2.1 Overview

Figure 1 illustrates the overall framework of the proposed method. We have divided it into two parts. The first part discusses parametric BIM modeling and how it can be used to automatically generate virtual BIM models. In the second parts, a viewpoint-guided labeled point clouds generation method is demonstrated, which is able to generate a labeled point clouds from a well-reconstructed BIM model. See Section 2.2 and 2.3 for details.

In the first step, we can convert the BIM model into mesh model by our own automated generation or existing BIM model. In the next step, we perform point cloud sampling on the mesh model. We perform random downsampling for the glass parts in order to obtain fewer point clouds for the glass parts so that the actual situation of LIDAR point cloud acquisition can be better modeled. In addition, the color of the sampled point cloud is also extracted from the original mesh material and transformed into a colored point cloud. In addition to having the point cloud of each individual part in the BIM model, we can assign a category tag value to each part according to its name, as well as assign a serial number tag value to distinguish the part from others of the same type, such as chair 1 and chair 2. In the third step, we need to merge the point clouds of all parts into one point cloud. Based on the N viewpoints generated in subsection 2.3.1, the viewpoints in this indoor point cloud are eliminated from the 360° field of view in both horizontal and vertical directions. In the fourth step we need to merge the indoor point cloud generated by each of the N viewpoints and remove the duplicate points. Finally, we separate the point clouds according to the attribute values of the part number labels of the points in the merged point clouds, and display the corresponding colors according to the category label values.

The 12 classes include structural elements (ceiling, floor, wall, beam, column, window, and door), furniture (table, chair, and sofa), and office items (bookcase and board). All other objects were annotated as ‘clutter.

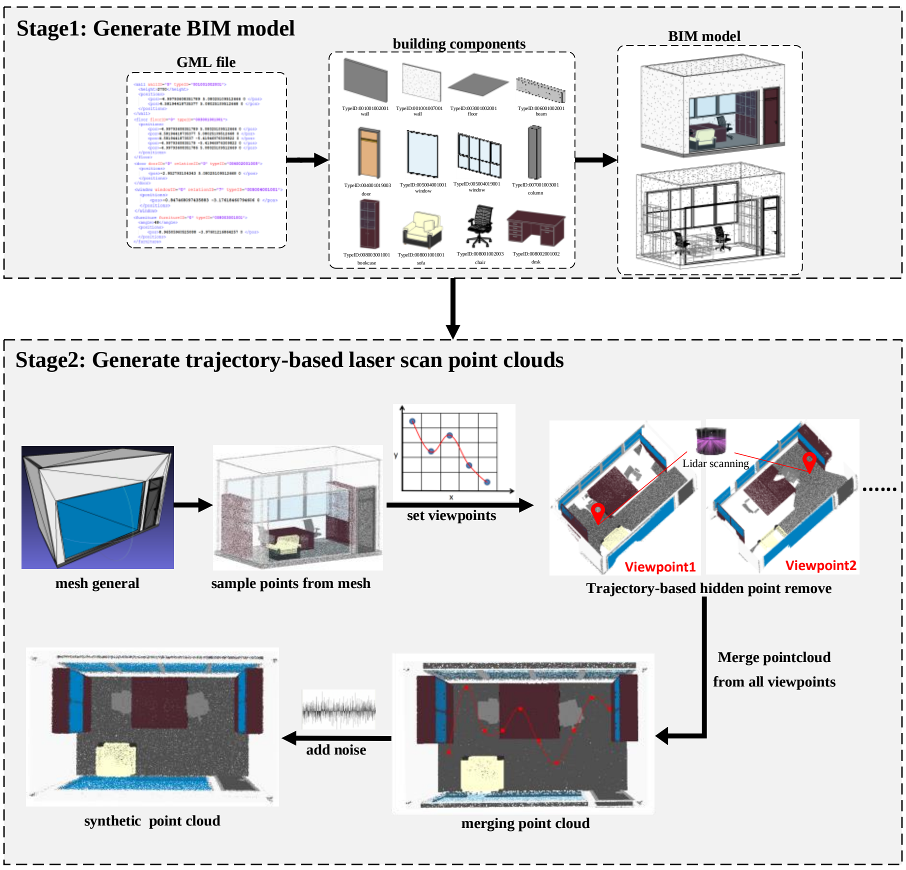
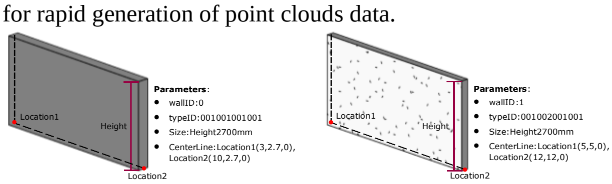


Figure 1. The overall framework of the methodology.

2.2 Parametric BIM modeling

In this framework, the BIM reconstruction is based on a parametric strategy, these parameters are used to define the size, location and type of BIM components. For example, as shown in Figure 2, the wall is reconstructed according to the defined typeID and the geometric parameters (Centerline and height). The style and thickness of the wall are defined using typeID, which is 001001001001 and 001002001001 in Sample 1 and Sample 2, respectively. The location of the wall is parameterized with a 3D line comprising two points, and the height of the wall is determined by the parameter of Size. Similarly, the locations of the Door, Window, Ceiling, Floor, Beam, and Column are defined by single points or sequences of points.Furniture is described parametrically by position, orientation and type. Therefore, based on the BIM parametric modeling method proposed in this paper, virtual BIM models can be constructed in large quantities and automated, and used for rapid generation of point clouds data.



(a) wall (sample 1) (b) wall (sample 2)

Figure 2. Parametric wall generation

2.3 Viewpoint-guided labeled point clouds generation method

2.3.1 Trajectory-based viewpoint point generation method: Simulate the trajectory of people walking in the aisle of a real scene, and set up different camera angles to simulate the workflow of scanning laser point clouds at rack stations based on the type of point cloud being scanned.

We simplify this process by first obtaining the minimum outer rectangular box of the interior point cloud. We set the viewpoint generation area to 80% of the interior of the minimum outer rectangular box in order to ensure that the viewpoint appears within the room. Then we divide the N×N grid in this rectangular area, and the coordinate origin is the lower left corner. Based on the assumption that the X-axis is longer than the Y-axis in this indoor data set, we will take the values in the X-axis direction with equal spacing, starting from the X coordinate of the center of the first grid. As a result, the viewpoint coordinates (X,Y,Z) are determined.

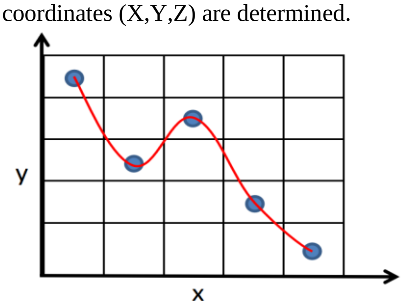


Figure 3. Viewpoint generation grid

In order to verify that the generated viewpoint is not located within the interior part, we will determine whether each randomly generated viewpoint is contained within the smallest outer rectangle of the interior part, and if it exists, we will take the random value of the generated viewpoint again and determine whether it is within the smallest outer rectangle of the interior part. We set a threshold value of T for the number of random values, if the number of random values exceeds T and is in the interior section, then we abandon setting this viewpoint; it may be occupied by furniture and may not be possible to place the acquisition device within this area.

2.3.2 Automated HPR-based semantic point cloud generation: By converting the BIM model into a mesh triangular model, we can sample the point cloud of each part individually on its surface to obtain the point cloud of each part. Following that, the point clouds of all the parts are merged to form the point cloud of the entire scene. Each part is assigned a category label and a unique serial number label value based on its serial number and type. The category label is used to identify the class of each point cloud, and the ordinal number label is used to distinguish between each component in the merged point cloud when used as a deep learning training dataset.

We then merge the point clouds with different viewpoints into a viewpoint-guided labeled point cloud. After merging the point clouds based on different viewpoints, a viewpoint-guided labeled point cloud is created.

2.3.3 Point cloud noise estimation: In order to make the point cloud closer to the accuracy of the real laser scanner acquisition device, we simulated the sensor scanning error by adding Gaussian noise to the point cloud to obtain a more realistic point cloud. The probability density function p of a Gaussian random variable z is given by:

$$\mathrm{pG}(z) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(z-\mu)^2}{2\sigma^2}} \tag{1}$$

where μ the mean value and σ its standard deviation. Therefore,a viewpoint-guided labeled point cloud generation method proposed in this paper can generate indoor 3D semantic datasets with complete labels and real measurement patterns ,and used for training deep neural networks for semantic segmentation of building point clouds.

3. RESULT AND DISCUSSION

3.1 Datasets and preprosessing

In this paper, the dataset used is generated based on GML rules and is derived from the BIM indoor dataset. As an example, the two interior BIM models are simulated as real scenes of offices. We created the two office BIM models using Revit and exported them as triangular mesh models in obj format. At this time, the vertex information includes information related to material color and object type. In the next step, we sampled the point clouds of each interior component triangular mesh model to get the point cloud of each component.

3.2 Single viewpoint rejection results

From Figure 4, we can see the results of Room1's final point cloud synthesis step in which 10 viewpoints are randomly generated based on the trajectory and the occluded point clouds are removed from the scene. It can be seen that the floor and wall point clouds that are obscured by the parts in the set viewpoint field are clearly eliminated.

3.3 Synthetic semantic point cloud results

Figure 5 shows the developed 3D model and a synthetic point cloud with full labels and true colors after viewpoint-based point guidance culling. Figure 6 illustrates the results of Room1 Room2's point cloud generation from the BIM model to the viewpoint-based guided labeling point cloud. Using the point cloud, it can be seen that 1) the type labels of each part are accurately retained in the point cloud, and 2) for parts such as bookcases, sofas, and tables that are adjacent to walls, the point cloud parts are eliminated since they are obscured. Furthermore, the point clouds at the bottom and inside the table, chair, sofa, and other parts are also excluded due to viewpoint occlusion. 3) The point cloud density of the window part is lower than other portions due to the material of glass, and the distribution will be more irregular. 4) The point clouds of the room as a whole are not equally spaced but contain noise perturbations that conform to the Gaussian distribution.

3.4 Discussion

3.4.1 Sensor error: The higher quality of the generated point cloud indicates that it is closer to the real point cloud. Laser scanners create point clouds by scanning the surface of objects with a laser beam, but the point clouds generated by these laser scanners are noisy, and our point clouds differ from the real point clouds in terms of noise. This paper includes a simulation of Gaussian noise generated by the sensor acquisition point cloud, but in practice, sensor noise can also be disturbed by factors such as the type of object, distance, etc., and a better simulation is required.

3.4.2 Type of object: The influence of the object material on the generated laser point cloud was considered, and the distribution of the point cloud was simulated with more random downsampling for the glass material than for the other components. It is important to note that many other materials are not taken into account, such as a window with not only glass, but also an iron frame. The laser scanner is affected by the material of the object when scanning its surface, as different materials absorb and reflect different amounts of laser light. This affects the density and distribution of the point clouds generated by the different object materials. This differences affects the segmentation algorithm, and the input data containing additional information may result in biased predictions.

3.4.3 Accuracy of 3D models: Depending on the accuracy of the material in the BIM model, the color of the point cloud will be more realistic. Whenever an object with multiple colors in a real scene has a single color in the 3D BIM model, then the color information of the point cloud is unreliable. In addition, the number of levels of detail in the 3D BIM model will also affect the similarity between the synthetic data set and the real data set. For instance, a pipe's secondary steel structure may be absent, and other parts, such as valves, may have less realistic point clouds (Noichl, 2021).

	viewpoints number	vertical field of view	horizontal field of view	before hide point remove	after hide point remove
ROOM1	10	360°	360°	1.68×10^6	1.35×10^6
ROOM2	10	360°	360°	1.52×10^6	1.25×10^6

Table 1. Synthetic point clouds parameters

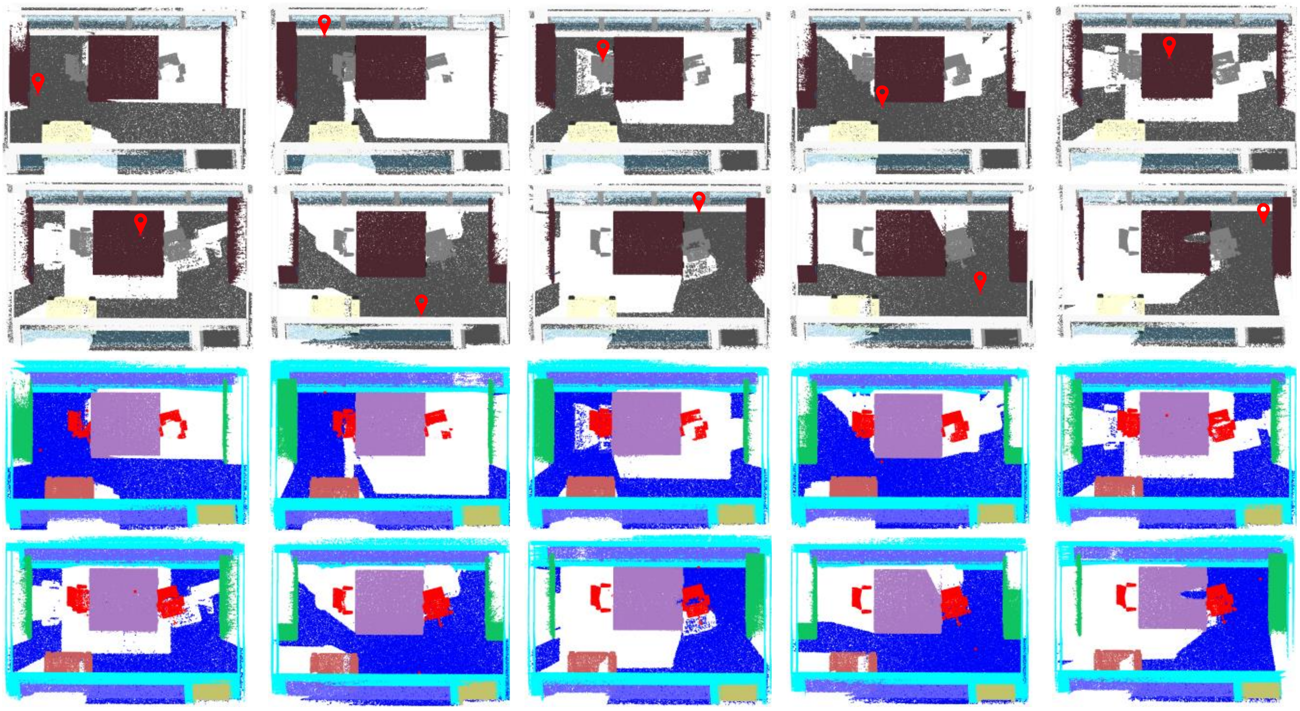


Figure 4. From top to bottom is the RGB, scale field image, from left to right is the result of the rejection of different view points in the scene

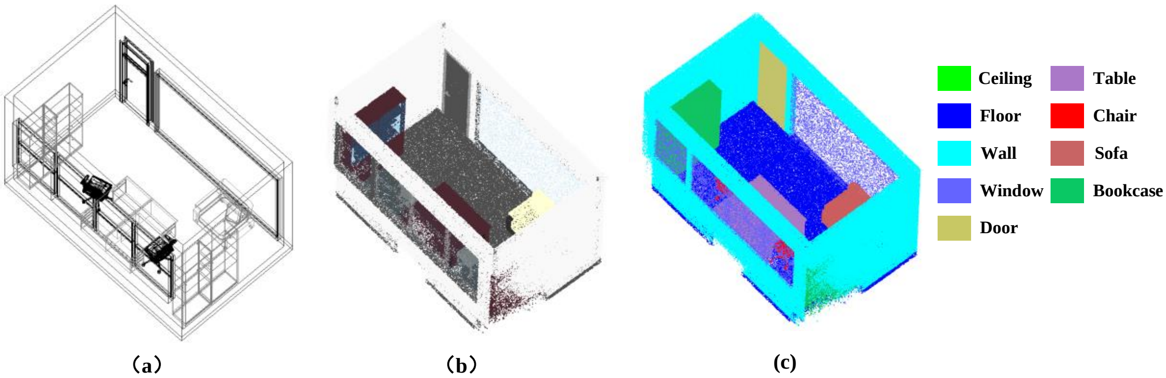


Figure 5. Office room1:(a)3D model generated from Revit,(b) synthetic point clouds with original color,(c) synthetic point clouds segmented by color with respect to 9 classes.

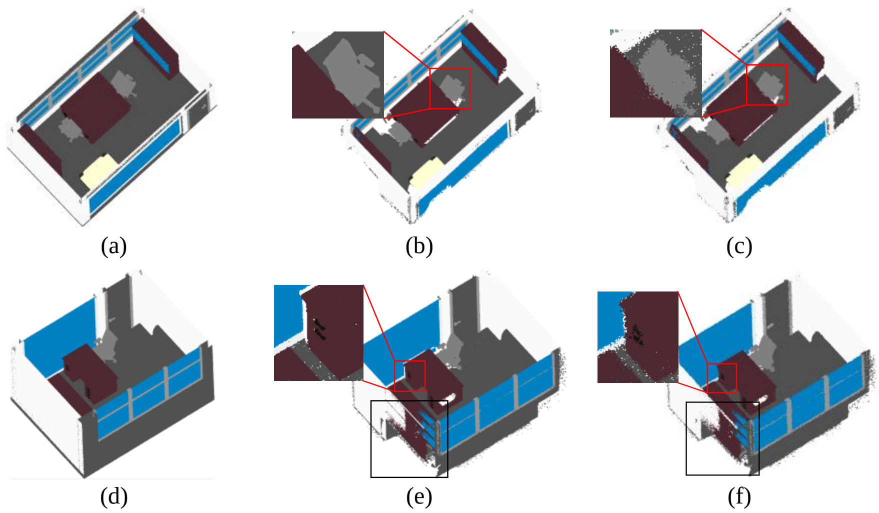


Figure 6. Visualization of the synthetic point clouds: reference point clouds(6a,6d), merging point clouds from each viewpoint (6b,6e), synthetic point clouds with Gaussian noise (6c,6f)

4. CONCLUSION

We present an automatic labeled point clouds generation based on parametric BIM modele. The core processes contains semantic mesh conversion from BIM, view-guided point cloud generation, noise simulation. Based on the method proposed in this paper, the 3D point cloud automatically generated is geometrically and semantically consistent with the laser data acquisition way, and some material information, such as glass is also considered. This method can greatly reduce the labor cost, while these labeled point clouds can be used for deep learning training to improve the semantic segmentation accuracy.

However, there are some shortcomings in this study that should be addressed in future research. At this stage we use Gaussian noise for noise simulation. It should be improved by integrating more accurate sensor error model for noise generation. Secondly,in this paper, only the reflective properties of the glass material are considered, more material information needs to be considered..

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