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Enhancing MEP Semantic Segmentation with Deep Learning and BIM-Synthetic Point Clouds

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Abstract

Semantic segmentation of point clouds with deep learning (DL) heavily relies on large datasets for training. However, there is a significant scarcity of datasets for Mechanical, Electrical, and Plumbing (MEP) scenes. To address this gap, this study proposes a method namely the ray-based laser scanning and intersection algorithm (RBLSIA) for automatically generating synthetic point clouds for MEP from Building Information Modeling (BIM) models. Based on RBLSIA, this study conducted totally 25 groups of comparative experiments, investigating the semantic segmentation performance on MEP scenes with different training datasets and different generation approaches for synthetic point clouds. The results show that: 1) the mean Intersection over Union (mIoU) with synthetic point clouds produced by the RBLSIA method is on average 3.32% higher than that by the uniform sampling method; 2) increasing the number of synthetic point cloud samples further improved both the OA and mIoU for semantic segmentation, even surpassing the training accuracy achieved with real point clouds.

1 Introduction

Building Information Modeling (BIM) has become a crucial tool in managing and maintaining building facilities. BIM provides comprehensive semantic and geometric information, which is essential for effective facility management. As-built BIM models, which capture the actual state of a facility, play a key role in improving maintenance and monitoring processes, thereby enhancing operational efficiency (Xiong et al., 2013).

Mechanical, Electrical, and Plumbing (MEP) systems are critical components of a facility. These systems require regular maintenance and renovation, particularly in older buildings. BIM models, which offer detailed information on MEP components, are highly valuable for these tasks. However, many existing MEP systems, especially in older facilities, do not have corresponding BIM models. Moreover, as-built conditions often differ from the original design plans, making frequent site surveys necessary to keep BIM models updated.

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In recent years, three-dimensional (3D) laser scanning, especially terrestrial laser scanning (TLS), has demonstrated high accuracy and efficiency in capturing detailed geometric data, making it an effective method for 3D reconstruction (Wang et al., 2022). A 3D laser scanner emits infrared laser beams and measures the distance to objects based on the reflected signals. By capturing distances from multiple angles, the scanner generates a complete set of point cloud data that accurately represents the 3D geometry of the scanned environment. However, point cloud data, while rich in geometric detail, often lacks semantic information, necessitating further processing to identify and classify objects within the data. Traditional object recognition methods, such as those based on geometric shape descriptors, hard-coded knowledge, supervised learning, or BIM-vs.-Scan (Wang et al., 2020), rely on predefined human knowledge and extensive parameter tuning. These methods become inadequate when dealing with MEP components that have extensive occlusions and irregular shapes.

Over the past few years, deep learning (DL) algorithms like PointNet and PointNet++ have demonstrated strong capabilities in processing point clouds for classification and segmentation tasks (Yue et al., 2024). By automatically learning complex patterns from large labeled datasets, DL reduces dependence on manually crafted features and enhances performance (Yin et al., 2021; Zhang et al., 2022). However, DL models typically require substantial training data. Unlike images, point cloud acquisition involves multi-station laser scanning, a process that is both time-intensive and labor-intensive. Moreover, annotating point clouds is significantly more challenging than labeling images. As a result, obtaining extensive labeled point cloud datasets is essential for DL-based model development.

To address data scarcity, BIM-based synthetic point cloud generation has been introduced as an efficient way to produce labeled point cloud data from BIM models, reducing the cost and effort required for data collection (Tang et al., 2022; Tang et al., 2023). Current research primarily focuses on generating synthetic point clouds for indoor building environments and bridges, leading to improvements in semantic segmentation accuracy (Lamas et al., 2024; Tang et al., 2023; Won et al., 2020; Zhai et al., 2022; Zhang and Zou, 2023). However, synthetic point cloud generation for MEP systems remains unexplored. It is still uncertain whether such synthetic data can enhance DL-based semantic segmentation accuracy. Furthermore, conventional uniform sampling methods may fail to capture real-world occlusion effects, highlighting the need for a more specialized approach to synthetic point cloud generation in MEP contexts.

To bridge this gap, this study introduces a method for generating synthetic point clouds from BIM models tailored for MEP scenes by simulating real laser scanning. The effectiveness of this approach is evaluated by comparing semantic segmentation performance across different synthetic point cloud generation techniques and training datasets.

2 METHOD

2.1 Proposed Method

This study introduces a method for generating synthetic point clouds for MEP scenes using BIM models. The overall workflow is illustrated in Figure 1. Initially, the BIM model is converted into the OBJ format, which is then processed using the Trimesh library in Python. Following this, synthetic point clouds are generated using the Ray-based Laser Scanning and Intersection Algorithm (RBLSIA). The detailed steps of the RBLSIA include three steps: Simulating Laser Scanner Positions, Setting Scanning Parameters and Error Simulation, and Intersection with Triangle Mesh.

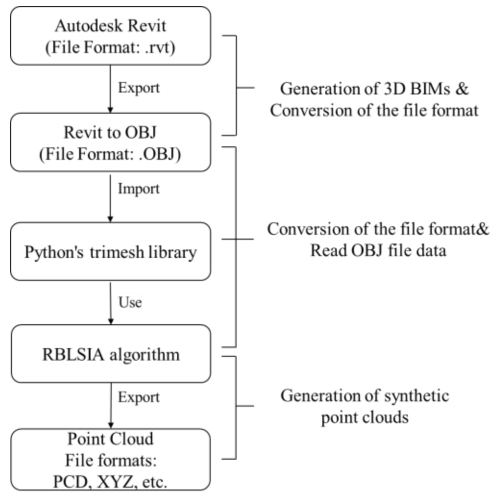


Figure 1: Process of generating synthetic point clouds for MEP scene from BIM

Simulating Laser Scanner Positions: The RBLSIA begins by simulating the positions of the laser scanner based on human-accessible areas. The scanner positions are chosen to avoid areas occupied by equipment such as pumps and tanks, while ensuring sufficient spacing between each scanning position.

Setting Scanning Parameters and Error Simulation: Next, the scanning parameters, such as vertical and horizontal resolution, are determined based on the actual specifications of the laser scanner. To simulate real-world conditions, measurement errors are also introduced. Synthetic laser rays are then generated accordingly.

Intersection with Triangle Mesh: The core of the RBLSIA is the Ray Intersections with Triangle Mesh (RITM) algorithm. This algorithm checks for intersections between each laser ray and the scene's triangle mesh. The closest intersection points are recorded and used to generate the synthetic point clouds. These points include relevant data such as material, color, and category. The pseudo-code for the RITM this method is shown in Algorithm 1.

Algorithm 1: Ray Intersections with Triangle Mesh algorithm

- intersection_points←[]
- For each *direction*∈D:
    - d_{min}←∞
    - For each mesh_part∈scene.geometry:
        - *h*←mesh_part.ray.intersects_location(*direction*)
        - If *h*:
            - $d \leftarrow \|h - P_s\|$
            - If $d < d_{min}$:
                - $d_{min} \leftarrow d$
                - closest_intersection←(h, material,color, category)
    - If closest_intersection:
        - intersection_points.append(closest_intersection)
- return intersection_points

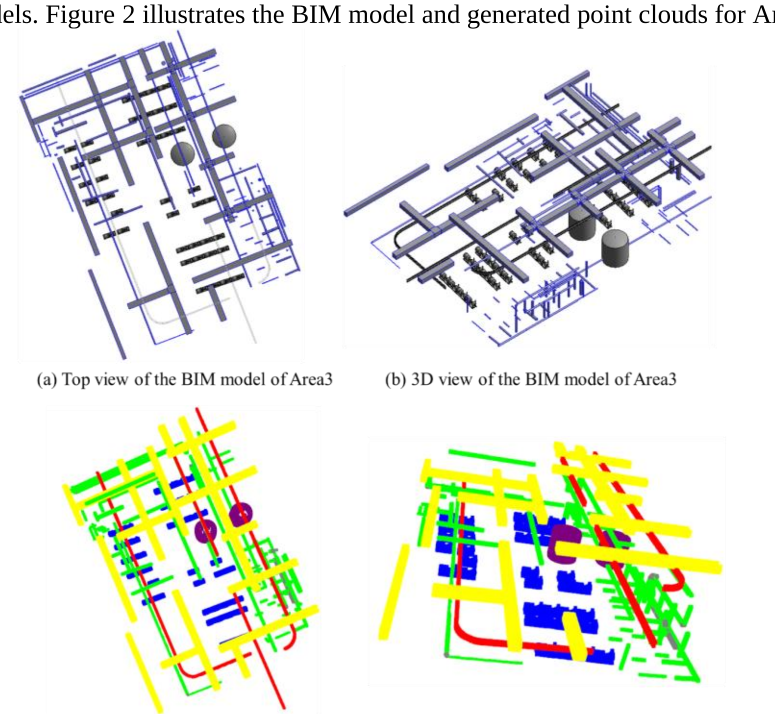
2.2 Data Preparation

The PSNET5 dataset (Yin et al., 2023) is used in this study to validate the proposed approach. The initial scene includes 500 million raw data points, covering approximately 3700 square meters, and consists of four areas with different scenes, as shown in Table 1.

Table 1. The number of points of each semantic category of the PSNET5 dataset.

Area	Scene	ibeam	pipe	pump	rbeam	tank	Total
Area1	CH	359,610	22,799,721	1,478,449	5,821,433	0	30,459,213
Area2	OSCG	467,782	5,712,622	5,712,622	2,488,327	5,455,825	14,404,173
Area3	SPH	3,023,003	8,408,907	2,455,212	9,055,639	1,523,331	24,466,092
Area4	WRT2	656,071	3,052,706	836,554	7,040,629	0	11,585,960
Total		4,506,466	39,973,956	5,049,832	24,406,028	6,979,156	80,915,438

In this study, synthetic point clouds are generated from the raw point clouds of Area1, Area2, and Area3. The raw point clouds are imported into Revit, where MEP components are modeled to create BIM models for each area. Subsequently, synthetic point clouds are generated from these BIM models. Figure 2 illustrates the BIM model and generated point clouds for Area3.



(a) Top view of the BIM model of Area3 (b) 3D view of the BIM model of Area3

(c) Top view of the generated point clouds of Area3 (d) 3D view of the generated point clouds of Area3

Figure 2: The BIM model and generated point clouds of Area3

2.3 Experimental Settings

This study employed ResPointNet++ as the DL algorithm (Yin et al., 2023). Each experiment was conducted over 100 epochs, utilizing the SGD optimizer with an initial learning rate of 0.01 and cross-entropy as the loss function. All experiments were performed on a single NVIDIA GTX 4090 GPU, with each set taking approximately 12 hours to complete. Due to the inconsistent color standards and varying reflections in MEP components, the input channels were limited to XYZ coordinates, excluding color information.

To evaluate the performance of DL models, three metrics were used: Overall Accuracy (OA), Intersection over Union (IoU), and mean IoU (mIoU). OA provides an overall measure of accuracy by indicating the proportion of correctly predicted points relative to the total. IoU assesses segmentation quality for each class by measuring the overlap between predicted and actual segments. In contrast, mIoU offers a balanced evaluation across all N classes, highlighting the model's consistent performance across different object types. The formulas for these metrics are presented in Equations (1), (2), and (3).

$$OA = \frac{\text{Number of correctly classified points}}{\text{Total number of points}} \tag{1}$$

$$IoU = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive} + \text{False Negative}} \tag{2}$$

$$mIoU = \frac{1}{N}\sum_{i=1}^{n} IoU_i \tag{3}$$

2.4 Experimental Design

The validation experiments include three parts. First, the performance of the uniform sampling method and the RBLSIA sampling method synthetic point clouds was compared. Second, the performance of semantic segmentation using with real point clouds and synthetic point clouds as training data was compared. Finally, the effect of increasing the number of synthetic point cloud samples on the semantic segmentation results was examined.

3 METHOD

3.1 Comparison of Different Generation Methods for Synthetic Point Clouds

This section aimed to compare the performance of two different generation methods for synthetic point clouds: uniform sampling method and RBLSIA sampling method. As shown in Table 2, five CGs (A to E) were conducted with different training sets and test sets, where some used purely synthetic data for training while some others used a mix of real and synthetic data for training.

According to the comparison results, it is clear that using synthetic point clouds generated by the RBLSIA method could always yield better model performance than using data from the uniform sampling method. On average, the RBLSIA method could achieve an improvement of 2.13% and 3.32% in OA and mIoU, respectively. Among all IoU metrics, the tank category showed the most significant improvement of 38.38%, followed by pump of 5.47%, rbeam of 2.41%, pipe of 1.55%, and ibeam of -1.76%. The substantial improvements in the tank and pump categories may be attributed to these being minority classes. For minority classes, more realistic synthetic point cloud features help in learning more accurate characteristics, thereby improving the precision of these categories. The average performance of the RBLSIA method on ibeam was slightly worse than that of uniform sampling. This is possibly because ibeam is relatively slender, making it difficult for the RBLSIA method to include its complete features, whereas uniform sampling is more likely to include complete features. Overall, the results demonstrate that the RBLSIA sampling method provides better model performance compared to uniform sampling method. Thus, the RBLSIA sampling method was adopted in the following experiments.

Table 2. Comparison between uniform sampled synthetic point clouds and RBLSIA sampled synthetic point clouds

CG	Exp. No.	Training set	Test set	OA (%)	mIoU (%)	IoU (%)				
						ibeam	pipe	pump	rbeam	tank
A	1	Area2 RBLSIA synthetic	Area3	**64.62**	**45.46**	56.45	48.74	0.02	69.23	64.62
	2	Area2 uniform synthetic	Area3	63.19	42.85	66.73	54.08	0	67.18	26.24
B	3	Area3 RBLSIA synthetic	Area4	**85.52**	**68.05**	98.30	50.58	26.14	97.19	/
	4	Area3 uniform synthetic	Area4	83.64	63.56	97.76	45.53	21.32	89.64	/
C	5	Area1 RBLSIA synthetic, Area3 real	Area4	**95.22**	**89.10**	95.97	85.22	78.76	96.46	/
	6	Area1 uniform synthetic, Area3 real	Area4	93.28	83.09	97.05	75.26	63.92	96.15	/
D	7	Area1+Area3 RBLSIA synthetic	Area4	**96.30**	**90.06**	95.23	84.89	81.41	94.79	/
	8	Area1+Area3 uniform synthetic	Area4	93.76	89.64	93.23	88.65	79.91	96.78	/
E	9	Area2+Area3 RBLSIA synthetic	Area1	**81.69**	**74.38**	68.67	87.04	74.03	67.79	/
	10	Area2+Area3 uniform synthetic	Area1	78.81	71.33	68.63	85.18	67.83	63.67	/

3.2 Comparison of Training with Real and Synthetic Point Clouds

This section compared the performance of training with real point clouds and synthetic point clouds of the same areas. As shown in Table 3, a total of seven CGs (F to L) were carried out. In each CG, DL models were trained separately with real point clouds and synthetic point clouds of certain areas, and the two trained models were tested on the real point clouds of another area.

According to the results, in all the CG except CG-L, training with synthetic point clouds resulted in lower OA and mIoU compared to training with real point clouds. On average, OA was decreased by 6.35% and mIoU was decreased by 10.84% when training with synthetic point clouds. Therefore, in most cases, the training effectiveness of synthetic point clouds was inferior to that of real point clouds, reflecting the differences between synthetic and real point clouds.

Table 3. Comparison between training with synthetic point clouds and real point clouds

CG	Exp. No.	Training set	Test set	OA	mIoU (%)	IoU (%)				
						ibeam	pipe	pump	rbeam	tank
F	11	Area3 real	Area4	**92.85**	**80.31**	97.06	73.23	53.89	97.05	/
	3	Area3 synthetic	Area4	85.52	68.05	98.30	50.58	26.13	97.19	/

G	12	Area3 real	Area1	**90.70**	**90.98**	79.76	96.87	97.54	89.77	/
	13	Area3 synthetic	Area1	77.21	49.74	45.58	74.11	28.12	51.15	/
H	14	Area1 real	Area4	**91.55**	**69.30**	39.13	79.56	66.40	92.11	/
	15	Area1 synthetic	Area4	82.49	56.15	39.29	47.73	50.25	87.34	/
I	16	Area1 + Area2 + Area3 real	Area4	**96.27**	**95.25**	97.01	91.96	95.06	96.98	/
	17	Area1 + Area2 + Area3 synthetic	Area4	88.22	75.49	64.72	79.43	61.61	96.19	/
J	18	Areal1 real	Area3	**77.00**	**64.82**	73.85	56.59	49.75	79.08	/
	19	Area1 synthetic	Area3	70.99	56.11	56.58	41.89	50.09	75.87	/
K	20	Area2 real	Area4	**71.57**	**35.37**	42.63	23.01	0.00	75.64	/
	21	Area2 synthetic	Area4	51.48	29.17	45.78	28.02	0.00	42.89	/
L	22	Area2 real	Area3	45.06	20.06	17.88	0.00	0.00	82.42	0.00
	1	Area2 synthetic	Area3	**64.62**	**45.47**	56.46	48.74	0.00	69.23	52.92

3.3 Comparison of Training with Real and Synthetic Point Clouds with Different Data Sizes

Results in the previous section showed that, with the same training data size, training with synthetic point clouds would achieve worse performance than training with real point clouds. However, one major advantage of using synthetic point clouds is its lower cost of generating labeled dataset. Therefore, this section aimed to examine whether it is possible to improve the model performance by increasing the training data size when using synthetic point clouds.

As shown in Table 4, totally five CGs (M to Q) were implemented. In each CG, the training set contained only one area when training with real point clouds, while the training set contained one or two areas when training with synthetic point clouds. In all the five CGs, it is found that training with synthetic point clouds of two areas could generate better performance than training with synthetic point clouds of only one area, with an average improvement of 13.91% for OA and 24.58% for mIoU. Hence, it is concluded that increasing the training data size could effectively improve the model performance when training with synthetic point clouds.

Among all the five CGs, three of them (CG-M, CG- N, and CG-O) showed that training with synthetic point clouds of two areas could yield better performance than training with real point clouds of only one area. This indicated that, with a larger training data size, purely using synthetic point clouds was able to achieve better performance than using real point clouds.

Table 4. Comparison between uniform sampled synthetic point clouds and RBLSIA sampled synthetic point clouds

CG	Exp. No.	Training set	Test set	OA(%)	mIoU (%)	IoU (%)				
						ibeam	pipe	pump	rbeam	tank
M	14	Area1 real	Area4	91.55	69.30	39.13	79.56	66.4	92.11	/
	15	Area1 synthetic	Area4	82.49	56.15	39.29	47.73	50.25	87.34	/

	23	Area1+Area3 synthetic	Area4	**96.30**	**90.06**	95.23	84.89	81.41	94.79	/
N	11	Area3 real	Area4	92.85	80.31	97.06	73.23	53.89	97.05	/
	3	Area3 synthetic	Area4	85.52	68.05	98.30	50.58	26.13	97.19	/
	23	Area1+Area3 synthetic	Area4	**96.30**	**90.06**	95.23	84.89	81.41	94.79	/
O	20	Area2 real	Area4	71.57	35.37	42.63	23.01	0	75.64	/
	21	Area2 synthetic	Area4	51.48	29.17	45.78	28.02	0.00	42.89	/
	24	Area2+Area3 synthetic	Area4	**89.52**	**70.84**	97.11	56.83	30.94	98.47	/
P	18	Areal1 real	Area3	**77.00**	**64.82**	73.85	56.59	49.75	79.08	/
	19	Area1 synthetic	Area3	70.99	56.11	56.58	41.89	50.09	75.87	/
	25	Area1+Area2 synthetic	Area3	73.42	56.77	46.75	55.13	53.13	72.09	56.77
Q	12	Area3 real	Area1	**90.70**	**90.98**	79.76	96.87	97.54	89.77	/
	13	Area3 synthetic	Area1	77.21	49.74	45.58	74.11	28.12	51.15	/
	9	Area2+Area3 synthetic	Area1	81.69	74.38	68.67	87.04	74.03	67.79	/

4 DISCUSSION

The proposed method provides a cost-efficient approach to generating training point cloud data and enhancing semantic segmentation for MEP scenes, which can play an important role in the maintenance and renovation of existing MEP systems in not only industrial plants but also other types of facilities. Without any real point cloud data, simply using synthetic point clouds generated from BIM models can obtain semantic segmentation models with certain accuracies. Specifically, according to the experimental results, training with synthetic point clouds of only one area could achieve an OA of 50% to 86% and an mIoU of 30% to 68% (refer to Table 3), and training with synthetic point clouds of two areas could further achieve an OA of 73% to 96% and an mIoU of 56% to 90% (refer to Table 4).

5 CONCLUSIONS

This study proposed the RBLSIA to automatically generate synthetic point clouds for MEP from BIM models. A total of 25 comparative experiments were carried out to evaluate the semantic segmentation performance across different methods for synthetic point cloud generation, and different training datasets. The experimental results indicated that: 1) the mIoU with synthetic point clouds produced by the RBLSIA method is on average 3.32% higher than that by the uniform sampling method; 2) increasing the number of synthetic point cloud samples further improved both the OA and mIoU for semantic segmentation, even surpassing the training accuracy achieved with real point clouds.

The results also reveal a gap between synthetic and real point clouds, particularly for components with significant differences between BIM models and real objects (such as pumps). Future research should focus on reducing these discrepancies to further enhance the quality of synthetic point clouds. Additionally, future studies can expand the range of MEP components (e.g., valves and fittings) and utilize different point cloud synthesis algorithms (e.g., diffusion models) to investigate the impact of various synthesis methods and component types on semantic segmentation accuracy.

6 ACKNOWLEDGMENTS

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