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AN AUTOMATED FRAMEWORK FOR GENERATING SYNTHETIC POINT CLOUDS FROM AS-BUILT BIM WITH SEMANTIC ANNOTATION FOR SCAN-TO-BIM

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ABSTRACT

Data scarcity is a major constraint which hinders Scan-to-BIM's generalizability in unseen environments. Manual data collection is not only time-consuming and laborious but especially achieving the 3D point clouds is in general very limited due to indoor environment characteristics. In addition, ground-truth information needs to be attached for the effective utilization of the achieved dataset which also requires considerable time and effort. To resolve these issues, this paper presents an automated framework which integrates the process of generating synthetic point clouds and semantic annotation from as-built BIMs. A procedure is demonstrated using commercially available software systems. The viability of the synthetic point clouds is investigated using a deep learning semantic segmentation algorithm by comparing its performance with real-world point clouds. Our proposed framework can potentially provide an opportunity to replace real-world data collection through the transformation of existing as-built BIMs into synthetic 3D point clouds.

1 INTRODUCTION

In the construction domain, numerous researchers from both academia and industry have invested in implementing computerized automation of as-built BIM generation (Bassier et al. 2016; Bosché et al. 2015; Jung et al. 2018; Kang et al. 2020; Koo et al. 2021; Son et al. 2015). A technological terminology used for this process is called Scan-to-BIM which consists of three components: 1) capturing an accurate information from physical realities through 2D and/or 3D scanning devices, 2) annotating the building elements with semantic classes characterized by a standard building taxonomy such as Industry Foundation Classes (IFC), and 3) creating 3D elements per semantics through modeling software.

In the context of indoor environments, a variety of building types have been explored by Scan-to-BIM researchers which include, but are not limited to: academic (Anagnostopoulos et al. 2016; Chen et al. 2019; Jung et al. 2014; Jung et al. 2018; Thomson and Boehm 2015; Wang et al. 2019a), structural (Bassier et al. 2016; Son and Kim 2017), residential (Barazzetti 2016; Wang et al. 2015), commercial (Rocha et al. 2020), and industrial facilities (Agapaki and Brilakis 2020). However, developed frameworks from individual studies are focused on specific building types, which implies that these methods would not be capable of showing the verified performance when applied across different domains having different types and distribution of object categories.

Deep learning algorithms developed in the computer vision community have been shown to interpret indoor and outdoor environments well, which includes object detection, identification, and semantic segmentation (Hackel et al. 2017; Huang and You 2016; Ioannidou et al. 2017; Landrieu and Simonovsky

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2018; Qi et al. 2017a; Qi et al. 2017b; Wang et al. 2019b; Zhou and Tuzel 2018). In terms of understanding the 3D visual scene, these tasks can be seamlessly integrated into the Scan-to-BIM framework for recognizing the building elements from the dataset collected from the construction domain. It is worth noting that a critical success factor for having successful performance when leveraging deep learning is sufficient amount of data for the deep learning model to be trained on, which guarantees the generalizability so that the trained model can be successfully applied to an unseen environment.

However, collecting datasets for Scan-to-BIM, especially achieving 3D scan data has explicit limitations. The 3D laser scanner itself is expensive and its operation is laborious and time-consuming due to heavy involvement of manual efforts for turning the scans into an understandable format for a machine. To avoid manual data collection and to facilitate deep learning application through a sufficient amount of training dataset, deploying synthetic datasets can potentially help automate the Scan-to-BIM framework preserving its generalizability. However, regardless of the types of algorithms being targeted, the process of generating a new dataset necessarily involves an annotation (i.e., semantic attachment) task where significant manual effort is required (Alm et al. 2005; Murthy et al. 2015; Wu et al. 2015). Moreover, it is very challenging to annotate 3D point clouds for several reasons: 1) the amount of points that vary depending on the spatial resolution of the given environment and 2) difficulties in visually understanding each point with human eyes.

This research presents an automated framework for generating synthetic point clouds from as-built BIMs where semantics are automatically attached to every single point leveraging standard building taxonomy. Two systematic approaches are illustrated to generate synthetic point clouds where Complete Synthetic Point Clouds (CS PCDs) refer to the point clouds generated using surface geometries of 3D BIMs and Realistic Synthetic Point Clouds (RS PCDs) refer to the ones generated by placing virtual laser scanners inside the 3D BIMs. RS PCDs are annotated in an automated manner with the semantics extracted from CS PCDs generation procedure. The viability of the generated synthetic point clouds is investigated by comparing the semantic segmentation performance between real point clouds using deep learning algorithm.

2 BACKGROUND

2.1 Synthetic dataset

A synthesizing approach allows for filling in missing data when real-world data is difficult to obtain. Some explicit advantages of using synthetic data are: 1) diversified and greater flexibility by simulating in a user-controlled environment, 2) complete annotation of the dataset avoiding errors in interpretation by human coders, and 3) cost-effective production compared to collecting real-world data.

In the context of Scan-to-BIM domain, Ma et al. (2020) made an initial attempt to leverage pre-existing BIMs to generate synthetic point clouds within a reverse approach using three commercially available software systems. Their experiments showed the effectiveness of synthetic point clouds especially when augmenting a small set of point clouds where a real-world dataset is limited, yet several limitations were identified as a future work. First, developing a new synthesizing approach is desired to generate more realistic synthetic point clouds. Synthetic point clouds generated from their methodology have uniform density across the regions while real point clouds are likely to show non-uniform distribution due to intrinsic factors such as occlusion and scanner motion. Also, manual efforts were involved for associating the semantics to the point clouds which acted as a bottleneck for automating the generation process. Lastly, 3D elements in BIMs were manually segmented prior to generating synthetic point clouds.

2.2 Annotation strategies

Raw point clouds achieved from scanning devices are generally represented by only geometric information (in a Cartesian coordinate system) or with color information, where semantic association is necessary for its utilization. This sub-section summarizes several strategies for annotating 3D point clouds.

Numerous open-source annotation tools have been developed in computer vision domain which aids in the annotation process by improving usability (Berger et al. 2018; Plachetka et al. 2018; Wirth et al. 2019;

Zimmer et al. 2019). However, these tools do not automate the annotation process which still requires significant manual efforts. Another approach is to leverage a pre-trained deep learning model for labeling new points. This approach can semi-automate the annotation task by reducing the manual process, which can be limited to only refinement. Also, unsupervised clustering can also be used to group the points having similar features without using any ground-truth information (Czerniawski and Leite, 2018). The grouped segments would be used as a guideline for human annotators to detect elements more easily as compared to browsing raw point clouds. However, all of the aforementioned strategies involve manual processes, which are naturally error-prone and have limitations in that they require considerable time and effort.

To further improve the synthesizing approach proposed by Ma et al. (2020), this study presents a fully automated framework to generate more realistic synthetic point clouds from 3D BIMs and to remove manual efforts involved for segmentation and annotation tasks. Synthetic point clouds generated from Ma et al. (2020) is referred to as CS PCDs while the ones generated from our new approach is referred to as RS PCDs.

2.3 Industry Foundation Classes

IFC is an open industry-wise standard that allows for communication and exchange of building information between project stakeholders. The information is stored in a standardized format which allows it to be shared using digital 3D platforms. IFC contains not only geometric information but also relationships between objects, attributes such as material type and its properties, and most importantly semantics such as object name, type, and unique ID.

3 METHODOLOGY

Figure 1 shows an overall framework developed from this research and the subsequent sub-sections provide more detailed descriptions for each stage.

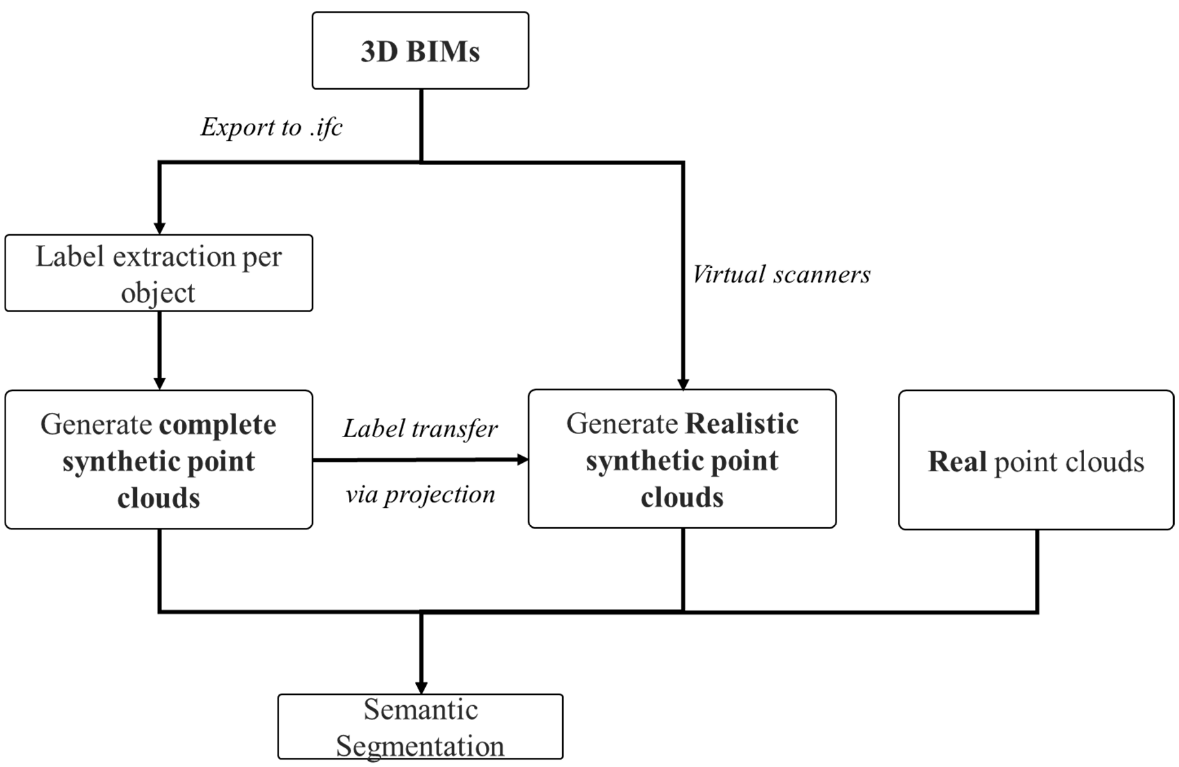

Figure 1: Overall framework for generating annotated synthetic point clouds and semantic segmentation using deep learning.

3.1 Semantics extraction via IFC format

Prior to generating CS PCDs, semantic information is extracted from the as-built BIM through the IFC format. Figure 2 visualizes building information of a mechanical room described in the IFC structure using IfcOpenShell (http://ifcopenshell.org/), an open source software library that helps users and software developers work with the IFC file format. As can be seen in the left side of the figure, each building element is characterized by its type, unique ID, geometric information, and all other available information in a defined hierarchy. Using IFC, an automatic element-wise segmentation can be performed with its label (i.e., type) attached through any compatible software systems or programming languages. This study adopted Blender (http://www.blender.org) for the segmentation.

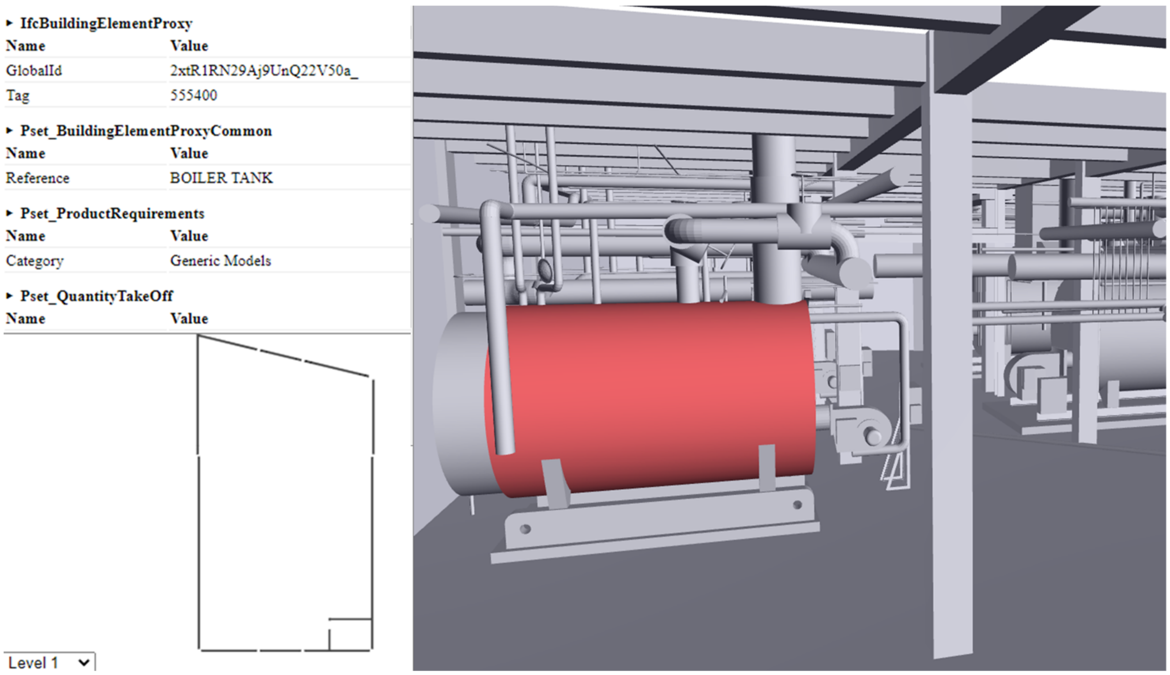

Figure 2: 3D illustration of a boiler tank in a mechanical room using IFC.

3.2 Complete synthetic point cloud generation

The extracted elements are converted into CS PCDs based on their surface geometries using commercially available software systems (Ma et al. 2020). CS PCDs are regularly spaced within a fixed user-defined distance.

3.3 Realistic synthetic point cloud generation

To generate RS PCDs, the manual scanning processes are simulated by placing virtual scanners in 3D space. Blensor (https://www.blensor.org/) offers multiple types of virtual scanners including Time-of-Flight (ToF) camera, LiDAR, and Kinect, among others. The parameters required per scanner can be specified via user preference. Experimental settings such as the position and orientation of the scanner need to be configured for generating RS PCDs (Figure 3). In this study, the scanner locations were designated by visually browsing the 3D models, and a total of 24 scans were created for each location – eight scans by rotating in top view and three scans by rotating in side view (i.e., Z-axis). The scanning protocol is automated with Python programming language (as shown in the below pseudocode).

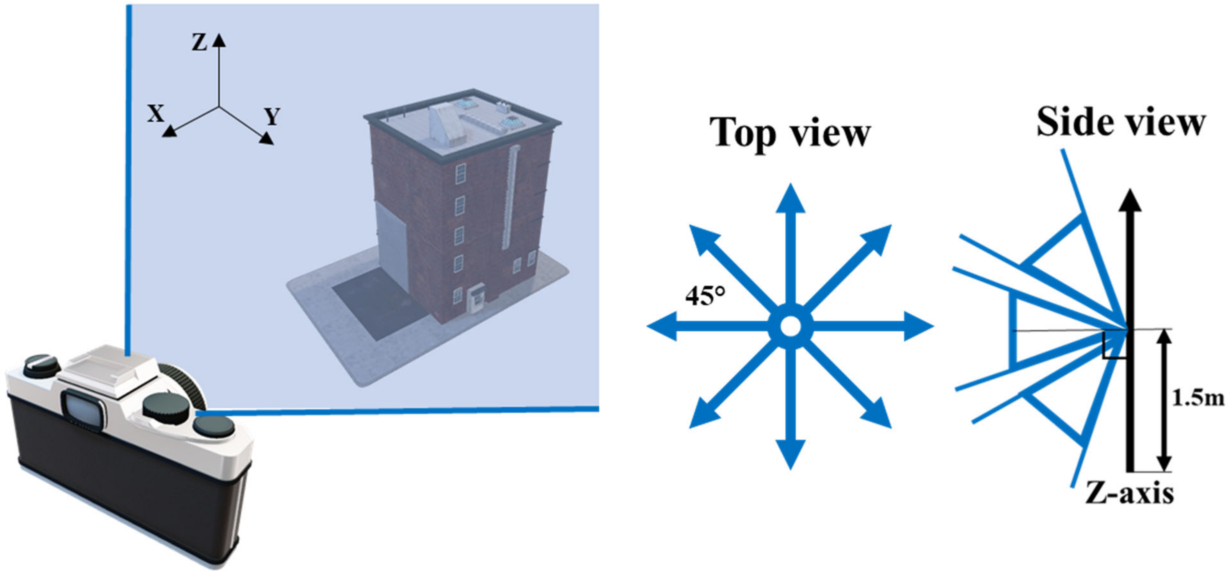

Figure 3: Experimental settings for virtual scanner.

```
procedure RSPCDs-GENERATION(S, R, E)
    s ← S // Load scanner location from CSV
    r_x, r_z ← R // X and Z axis rotation angles
    E_sc, E_res_x, E_res_y, E_dist ← E // Scan environment variables (scanner type,
                                         x and y resolution, and scan distance)

    for s do
        for r_x, r_z do
            blensor.tof.scan_advanced(s, r_x, r_z, E_sc, E_res_x, E_res_y, E_dist)
        end for
    end for
end procedure
```

3.4 Label transfer via projection

An ideal solution for automatic annotation is to directly attach the semantics of the as-built BIMs to the synthetic point clouds during the virtual scanning process. However, it is hardly achievable within the embedded functions in the software systems that this study circumvents the problem by leveraging k-nearest neighbor algorithm using annotated CS PCDs. The CS PCDs and RS PCDs have the same coordinate system which eliminated the need for registration.

3.5 Semantic segmentation using deep learning

To investigate the viability of the generated synthetic point clouds, PointNet (Qi et al. 2017a) is chosen as a deep learning semantic segmentation algorithm. This algorithm allows direct consumption of raw point clouds for the prediction of semantics for each point. The semantic segmentation performance was measured by calculating Intersection-over-Union (IoU) per object which represents a balanced value of precision and recall.

3.6 Dataset

In this study, the Stanford Large-Scale 3D Indoor Spaces (S3DIS) was selected as a benchmark dataset (Armeni et al. 2016). This dataset contains point clouds for six large indoor areas having a total of 271 rooms. Among the six areas, 44 rooms in 'Area 1' were referenced to model the as-built BIMs and the real point clouds of 40 rooms in 'Area 2' were used as a testing dataset.

4 RESULTS

4.1 Complete and realistic synthetic point clouds

As a result, for RS PCDs, ~19 million points were generated from the as-built BIMs for Area 1 in S3DIS dataset which consists of 44 rooms including: 31 offices, 8 hallways, two conference rooms, once copy room, one pantry, and one restroom. Synthetic point clouds were generated for 12 semantic classes that include structural elements, furniture, and office items. Figure visualizes the as-built BIMs, real point clouds, and synthetic point clouds for three rooms. Visual inspection illustrates that the CS PCDs are uniformly distributed while RS PCDs better resemble real point clouds in terms of sparseness.

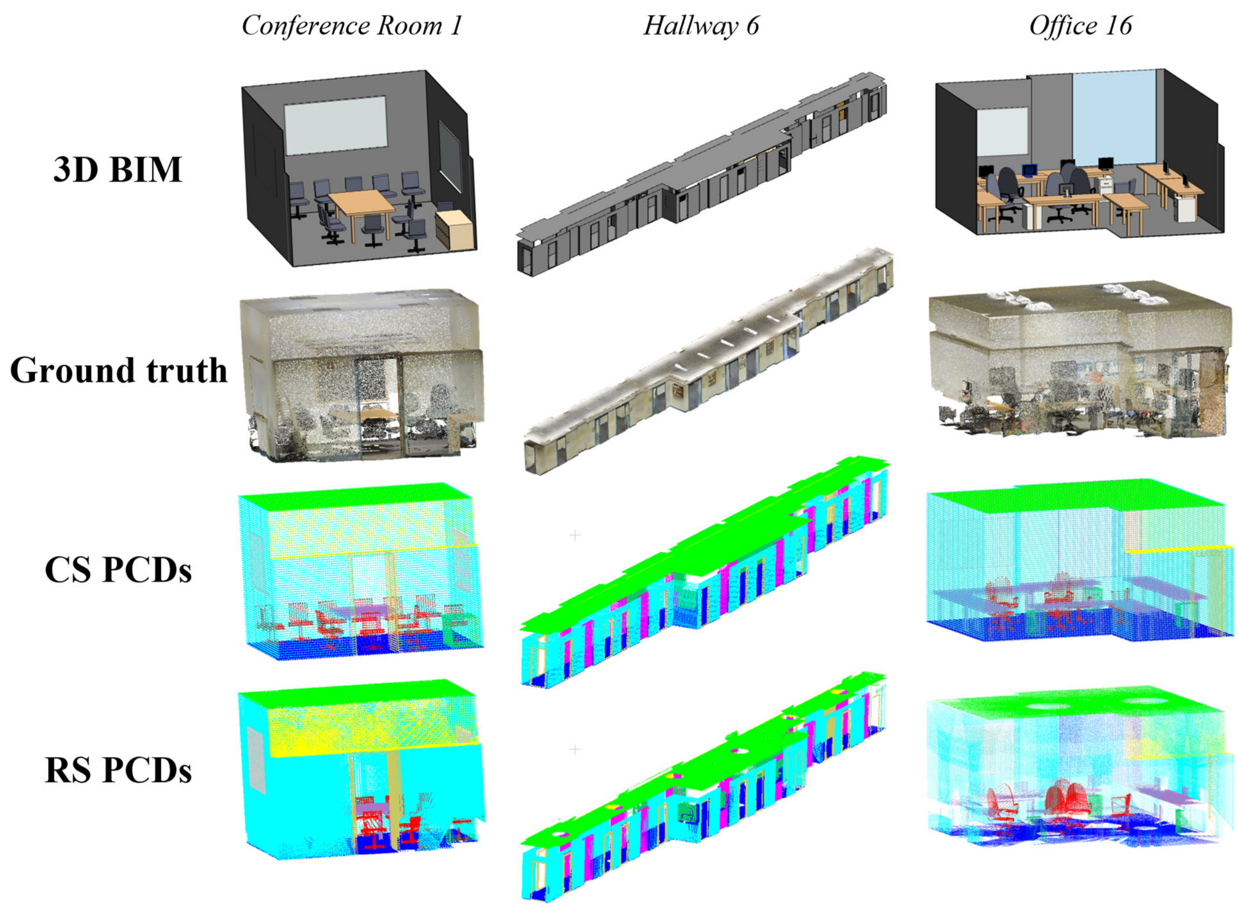

Figure 4: CS PCDs and RS PCDs generated from as-built BIMs. The ceiling and front walls of 3D BIMs were hidden for visual clarity.

4.2 Semantic segmentation performance

In order to quantitatively measure the effectiveness of the generated dataset, semantic segmentation was performed using PointNet. For the input data, a six dimensional feature set of x, y, and z and normal vector was computed. Table 1 summarizes prediction performance for each object when trained on three types of datasets.

For an overall accuracy, real PCDs, CS PCDs, and RS PCDs showed 51.33%, 40.72%, and 45.61%, respectively, indicating that RS PCDs showed in average 4.89% improvement over CS PCDs from 12 semantic classes. Comparing the performance of CS PCDs and RS PCDs, RS PCDs showed better performance in most object categories, and, in particular, a significant improvement was observed for windows and boards. This observation confirms that some of the volumetric issues identified in Ma et al. (2020) were resolved. However, doors and tables showed relatively inferior results than CS PCDs. The class distribution of our synthetic datasets revealed that the proportions of door and table objects in RS PCDs compared to CSPCDs were reduced by 4.97% and 1.74%, which contributed to performance degradation.

Compared to real PCDs, lower accuracies were achieved for most object categories and several performance limitations remain with the synthetic point clouds. First, as mentioned in Ma et al. (2020), the as-built BIMs used in this study do not have the enough detail as compared to real-world environments. Also, as can be seen in Figure 5, due to the elements not being modeled in the as-built BIM, the occluded parts are different from the real dataset which contributes to observed discrepancies. Also, there would be insufficient scans for RS PCDs which would fail to train the model to identify certain types of objects. However, it is expected that setting up an experimental configuration would resolve this issue through dataset expansion.

Table 1: Semantic segmentation performance comparison using PointNet

	Ceiling	**Floor**	**Wall**	**Beam**	**Column**	**Window**
Real PCDs	80.38	86.03	65.99	65.59	32.85	40.20
CS PCDs	70.36	65.76	61.33	69.93	10.08	3.02
RS PCDs	**76.56**	**77.05**	**63.26**	63.53	**33.08**	**21.77**
	Door	**Table**	**Chair**	**Sofa**	**Bookcase**	**Board**
Real PCDs	19.48	68.95	76.64	28.64	41.49	9.69
CS PCDs	29.17	73.89	56.71	3.74	44.41	0.23
RS PCDs	21.97	53.94	**77.14**	2.22	**47.17**	**9.66**

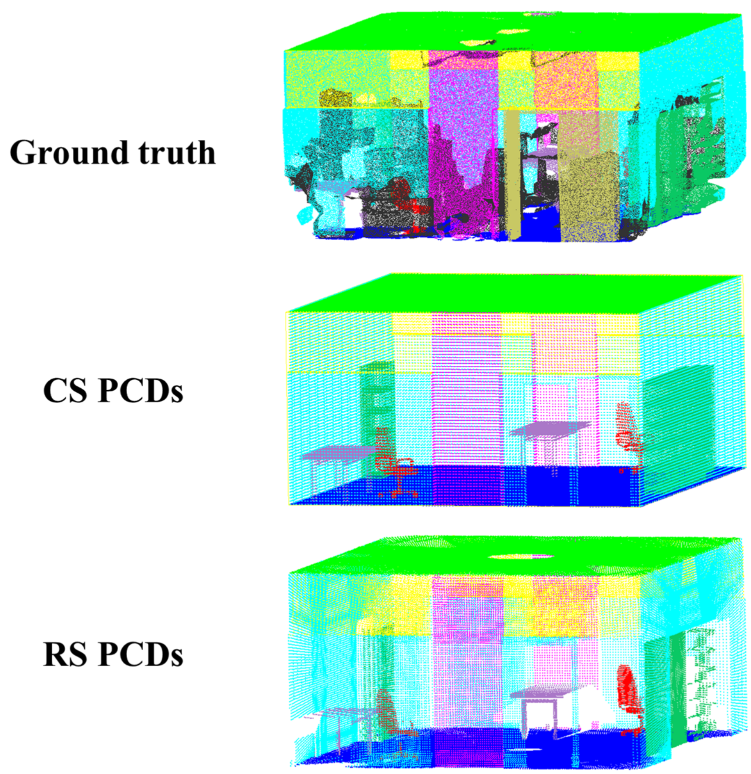

Figure 5: Distinct dissimilarities between real and synthetic data.

5 CONCLUSION

This paper presented an automated framework for generating synthetic point clouds from as-built BIMs where semantics were automatically annotated via IFC file format. A detailed procedure is provided by showing visual graphics and implementation method. In addition, the viability of the generated synthetic data was identified by deep learning semantic segmentation model, which showed 4.89% overall accuracy improvement compared to the synthetic dataset developed in previous study by increasing similarity between the synthetic and real datasets. Our fully automated framework can help researchers reduce manual efforts related to attaining a dataset when opportunities to scan the real-world are limited. In addition, with the advantage of being able to generate infinite amount of dataset given as-built BIMs, our framework contributes to a step-wise advancement for developing such a generalized semantic segmentation algorithm which can be applied to interpreting multiple types of building environment.

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