
From Point Cloud to as-built BIM: Semi-automated Wall Reconstruction for Dismantling of Nuclear Power Plants

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Abstract

Germany has decided to phase out of nuclear power plants by the year 2022. Therefore, the efficient decontamination and dismantling of building structures are widely considered to be one of the most important aspects to reduce the low-radioactive waste and process uncertainty. Although many robotic systems have been developed to investigate and scan in hazardous environments, the scanned information in point clouds lacks the ability of information exchange and –integration. Building Information Modelling(BIM) can provide a platform for 3D model visualization as well as information management. However, manual transformation from point clouds into BIM is time-consuming and error-prone. This paper proposes a semi-automated methodology to transform building structures from point clouds to an as-built BIM Model. In order to extract the features from point clouds, the maximum likelihood estimation algorithm based on a non-parametric approach is used. The BIM Model is then partially automatically generated using extracted features and scripts created by visual programming language. A further development integrates the results from contamination measurement in the model for visualization. The paper concludes with a summary and an outlook of future investigation directions.

Keywords: Building Information Modeling, as-built BIM, Point clouds, 3D Reconstruction, Automation

1 Introduction

There have been discussions about phasing out nuclear power plants in Germany since 2000. According to the 13. Amend of the atomic energy (AtG) laws, the nuclear power plants in Germany will be step by step decommissioned by the end of 2022 [1] [2]. With the gradually increasing number of demolished nuclear plants, one of the main challenges is how to decontaminate and dismantle the closed nuclear power plant efficiently. The core objectives of this process can be listed as follows: protection of the workers and the environment, waste minimization, and cost optimization[3]. It is necessary to reduce the risk to humans during decontamination work according to ALARA (as low as reasonable achievable) principle. Since robot systems are helpful to carry out tasks in hazardous environments, an increasing number of researches are carried out in aspect of robot systems in hazardous environments.

To achieve autonomous or semi-autonomous decontamination, it is necessary to explore the unstructured and hazardous environment at the beginning. For this purpose, a robot platform was jointly developed by our institute and the Institute of Intelligent Process Automation and Robotics Lab [4]. A high-resolution 3d Laser Scanner Focus S150 from FARO is used to investigate the unknown environment. Furthermore, many additional information such as thermal images, gamma spectroscopy measurements can be stored in the platform [5]. The scanned data are processed using the commercial software FARO SCENE into a point cloud, which is a 3D documentation of the building structure. However, the scanned information in point clouds lacks the ability of information exchange (such as the material of the wall and so on) and integration. Meanwhile, the lacked information is crucial for the decontamination and further project plan. How to combine the point cloud and information is the first problem we need to solve. As the foundation of digital transformation platform in the architecture, engineering, and construction (AEC) industry, Building Information Modeling (BIM) can perfectly overcome this problem. BIM can provide a useful platform for creating and managing information, which can be used for energy analyze or project planning [6]. BIM has the ability to provide not only a 3D geometry model of the building components but also a comprehensive set of semantic information. Therefore, when compared with point cloud 3D model, BIM can provide not only a 3D model but also a planning tool for logistics, simulation, evaluation and documentation in the decontamination workflow. In order to use BIM platform for logistic planning in decontamination projects, it is necessary to transform the point cloud model into a BIM model. However, manual transformation from point clouds into BIM is time-consuming and error-prone. This paper proposes a semi-automated methodology to transform building structures from point clouds to an as-built BIM Model for dismantling nuclear power plants.



The paper is composed of five chapters, including this introductory chapter. At first, a literature review of the development of reconstruction methods and the situation of BIM in deconstruction is conducted. Chapter three begins by laying out the developed methodology for processing of point cloud and semi-automatically generating of BIM model. Furthermore, a method for visualizing the measured radiation results in BIM model is introduced in this chapter. The use case and results are shown in the fourth chapter. The last section provides a summary, which contains the main contributions of this paper and areas for further research.

2 Related Work

The reviewed researches in the paper can be divided into two parts: BIM in deconstruction and dismantling, 3D Reconstruction from point cloud to BIM. Literatures in these fields are described in subsections 2.1 and 2.2.

2.1 BIM in Deconstruction and Dismantling

Since now, the BIM technology has been used widely for visualization, design coordination, process monitoring, and facility management [6]. However, there are not many studies in deconstruction. Recently, with rising emphasis on environment protection, more and more attention is focusing on effective demolition and deconstruction. Circular Economy [7] pointed out that using appropriate information management tools such as BIM, the process of the pre-deconstruction can be effectively audited. The advantage is that the potential of reuse and recycling can be rapidly and accurately assessed. Akbarnezhad et al. [8] demonstrated that various deconstruction strategies can be evaluated on a BIM model in aspects such as cost, energy use, and footprint, so that the most sustainable strategy can be chosen. Similarly, Cheng [9] developed a waste estimation system using BIM technology. In their introduction to the developed system, the information about waste management can be stored in a model. Therefore, the waste during demolition can be accurately quickly and automatically estimated in the model. Volk et al. [10] claimed that with the intensive BIM application in existed building, the number of facility management interfaces for existed BIM model is growing, while the research for deconstruction functionalities is still limited yet. In the research, it was also pointed out that the main challenges for BIM application for the existed building was how to capture the building data and create BIM models automatically. In 2020, Akbarieh et al. [11] reviewed the literature from the period and analyzed the current development and challenges in BIM-based End-of-Life planning. In the major study, several important points in BIM-based deconstruction were discussed, such as challenges in culture, society, and technology as well as the connection between BIM and other waste management software.

2.2 3D Reconstruction from point cloud to BIM

Many researches have studied on reconstruction of building interiors and exteriors using laser scanner. Tang et al. [12] have reviewed the overall process of creating as-built BIMs. The core operations include geometric modelling, object recognition, and object relationship modelling. The most common used method of planar surface detection is Hough transform or RANSAC algorithm. Recently, Xu [13] also provided a thorough review of the state of the art acquisition and processing techniques for building reconstruction using point clouds. In Thomson's [14] research, the plane detection was done with the open source software Point Cloud Library (PCL) implementation of RANSAC. After that, basic Industry Foundation Classes (IFC) geometry was reconstructed from segmented point clouds automatically. More and more researchers are trying to investigate self-developed algorithm for reconstruction. Anagnostopoulos et al. [15] developed a robust framework to cluster the point cloud from an entire building into floors, walls, and ceilings. The planar surface was firstly segmented using the RANSAC algorithm and then classified into different objects according to its features. Macher et al. [16] did a series of researches on how to transform the building structure from a point cloud model into BIM model semi-automatically. The process included plane segmentation, point classification and BIM model reconstruction. Instead of using the RANSAC algorithm, a more precise algorithm with the same sampling strategy was used for plane segmentation. After that, the points were classified into different objects. To create the BIM model, the extracted structure was firstly transformed into .obj format and then created an IFC file using the FreeCAD software. [16] However, using RANSAC may cause so called 'bad-segmentation' problems. The reason is that points constituting the maximum consensus may be derived from different objects according to Previtali's research [17]. In this research, the developed strategy was paid to minimize this problem by including topology measure in the segmentation process. Another widely used method is Hough Transform. Adan and Huber used 2D histogram to create a horizontal plane image [18], from which all surfaces were extracted using a Hough Transform. To better overcome the problem with cluttered and occluded environment, Mura et al. combined the operation process both in 3D space and in 2D projection [19]. The basic room detection was performed in the 2D projection, while the patch detection and the occlusion based pruning and the final fitting were performed in 3D space.

With the rapid development of artificial intelligence, many machine learning technologies can be used for scan to BIM. Bassier et al. [20] presented a method using random forests to identify and classification of structural elements automatically, which showed a good performance in feature labeling in different buildings. Similarly, Sahebdivani et al. [21] used the PointNet deep learning network for semantic segmentation in the point cloud data. The PointNet neural network is a novel type of neural network developed in 2017 [22] for object classification and segmentation of 3D point cloud data.



3 Methodology

The input data for the developed method is the registered point cloud data as well as the measured radiation results from the robot. The developed approach can be divided into four steps. The following diagram shows the overview of the method. The first three parts are reconstruction of building structures from point cloud to BIM model. The last part is the integration of the radiation results in the built model from the first part.

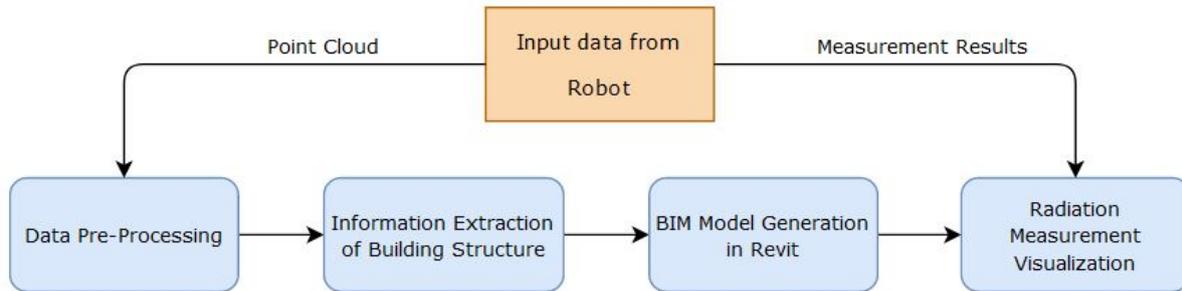


Figure 1: Overview of the methodology

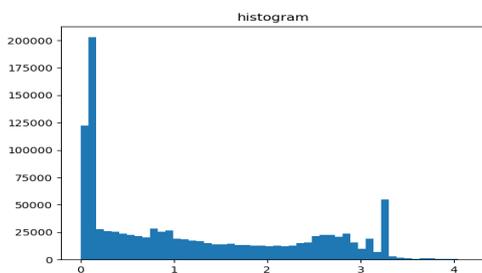
3.1 Point Cloud Data Pre-Processing

The method used the unstructured point cloud data. Therefore, it is required to pre-process the data. The aim of this step is to remove the noise points, which don't belong to the building. Furthermore, the 3D point clouds are rotated to a proper angle for the wall information extraction. In order to save time during the process, the point clouds are re-sampled at 1 cm.

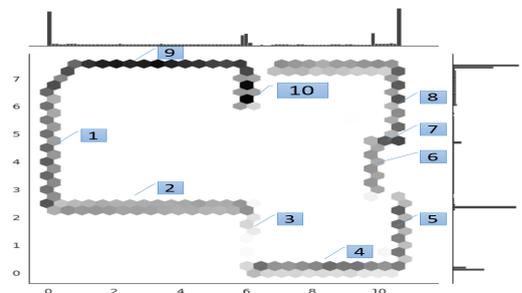
3.2 Building Structure Segmentation

The point cloud data can be regarded as a big multi-modal data set containing the position information in the x, y, and z axes. According to Pattern Recognition and Machine learning [23], the non-parametric approach is the main method used to investigate the distribution of multi-modal data sets. The most common application of the non-parametric approach is the histogram method. One beneficial of the histogram method is quickly visualization of the data distribution in one or two dimension. Therefore, the histogram was used in the algorithm to visualize and identify the data distribution. The key point of using the histogram method is how to choose the bin width properly. For a good result, the value should be neither too large nor too small. After getting the overview of the data distribution, the next step for information extraction was to find the possible location of the building structure. To determine the position, the maximum likelihood estimation was then implemented in the algorithm. The overview of the whole algorithm is shown in following figure 3.

The structure of a point cloud model can be divided into four main categories, which are floor, ceiling, wall, and the objects placed in rooms. To make the process of extracting information as less complicated as possible, the building structure is segmented



(a) Histogram in z-axis



(b) Histogram in x- and y-axis

Figure 2: Histogram

from the whole data-set at first. Figure 2(a) shows the distribution of the whole points in z-axis. As the figure shows, the point cloud data of floor and ceiling have a significantly high probability in the z axis, so the histogram of the whole data in z-axis was used for floor and ceiling segmentation. Once the position of the floor and ceiling is determined using maximum likelihood estimation, the points belonged to the ceiling and floor are removed. After that, the remaining point cloud data only included wall structure and stuffs placed in rooms. However, the method used for floor and ceiling segmentation is not suitable for wall segmentation. Since many objects in rooms are also scanned in the point cloud, it is difficult to identify whether the point belong to the wall or not. To solve this problem, the points, which are 30 cm nearest to the ceiling, were selected for further analysis and then used for investigating the positions of wall structures. Similar as before, the non-parametric approach together with maximum likelihood estimation was applied. As shown in figure 2(b), which is different from before, the histogram was implemented in x- and y- axis. After visualizing the distribution, the most potential position of the walls in x- as well as in y-axis is analyzed by using maximum likelihood estimation. The detected walls are numbered in the figure 2(b). Until this step, the length of each wall is still uncertain. Since there may exist two or more wall structures at the same potential position, getting the maximum and minimum point of the points at the potential position is not suitable. Therefore, a middle point search algorithm was implemented on the other axis at each potential position. In the end, the detected start and end points of each wall structure were stored in a text file.

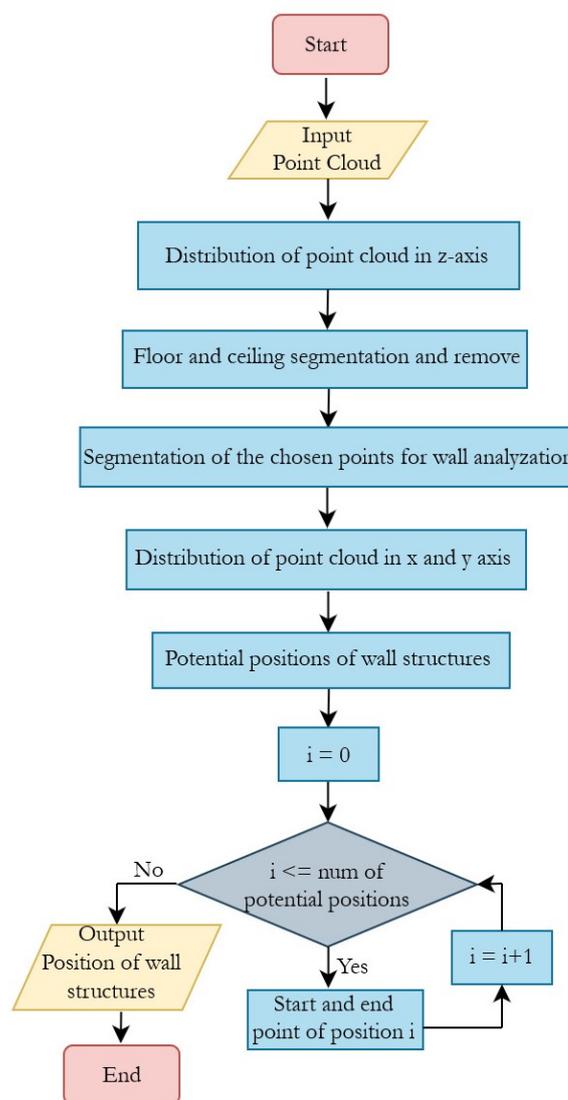


Figure 3: Overview for the developed algorithm

3.3 BIM Model Generation

A BIM model of the building structure was created based on the extracted information in this step. The software Revit is used for building the model. Instead of establishing the model only with Revit, a more efficient method was implemented for modeling, which is parametric design with Dynamo visual programming for Revit.

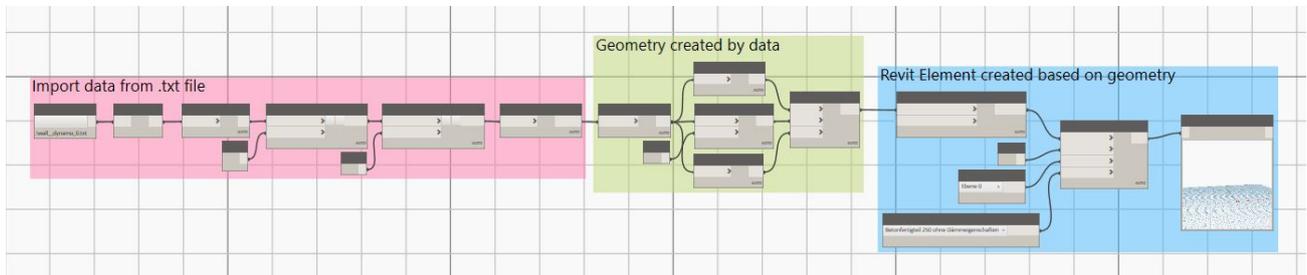


Figure 4: Diagramm of Dynamo

The figure 4 demonstrates the BIM model generation process. The extracted wall information is imported into dynamo at the beginning. Once the list of imported data is created, the geometry curve of each wall structure is generated. Finally, a Revit wall element is created based on the geometry and the element type. Since every wall element can be created using the same processing method, a more automated and efficient way is implemented in this step. Instead of filling the required information separately, a python script with a loop function is written in dynamo to create all wall elements automatically.

3.4 Radiation Measurement Visualization

As introduced before, a BIM model supplies a platform for information management and documentation. During the dismantling of the nuclear power plants, radiation measurement plays a key role in decontamination of building structures. When a building structure has contamination, the waste of the building structure should be classified as hazardous waste. With the given information of contamination, the structure can be firstly decontaminated and then deconstructed, which can reduce the amount of the hazard waste. Otherwise, the waste of the whole deconstructed objects should be regarded as hazardous waste. Therefore, it is useful to integrate the measured radiation results in the built Revit model. The advantage of the result visualization is that the distribution of the contamination in the wall structure can be directly observed, which provides guide information for robot systems to remove the contaminated part. To achieve this function, a package named Ladybug in dynamo is used. After importing the measurement results together with their location in dynamo, the results can be visualized on the related element in Revit. The color is based on its measurement values. At the place where the radiation value is higher than the critical value, the color will be set to red. Otherwise, the color will be set to blue.

4 Case Study and Result

To test the developed approach, an infrastructure named Living-Lab in the institute of management and construction is used for the case study. The Living-Lab is provided as a realistic test environment to carry out decontamination scenarios. Figure 5(a) shows an overview of the Living-Lab. The Living-Lab was firstly scanned by FARO Laser scanner and then registered to a point cloud data in the FARO SCENE software, which was used as input data for the proposed method. The point cloud model after pre-processing is shown in figure 5(b).

In the step, where the information of building structures can be extracted, the floor and ceiling were segmented and removed at the beginning. Figure 6(a) presents the remaining point cloud data, which includes the wall structures and objects placed in the room.



(a) Overview of the Living-Lab

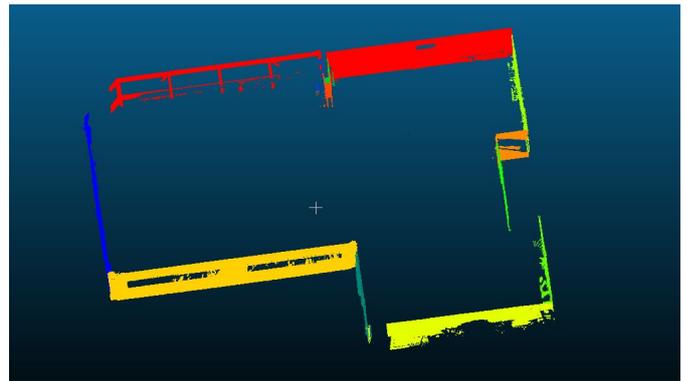


(b) Point cloud data of the Living-Lab

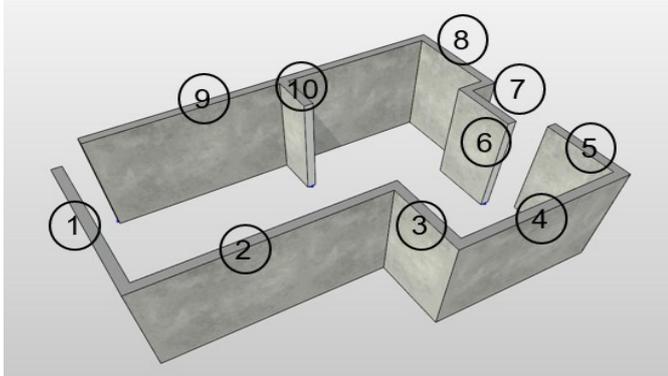
Figure 5: Figures of Input



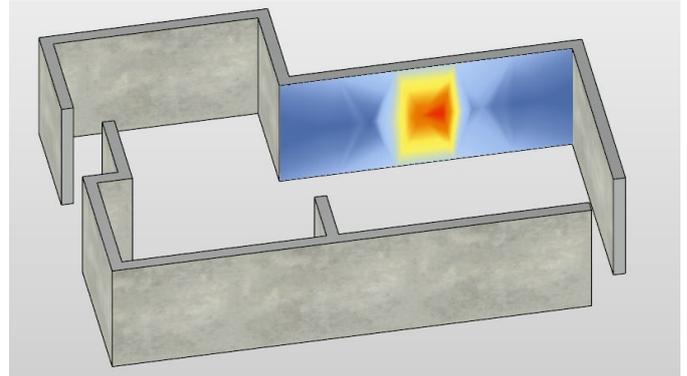
(a) Point cloud of the walls and objects



(b) Point cloud of the extracted walls



(c) Semi-automated generated BIM model



(d) Measurement result visualization

Figure 6: Figures of Results

The results of the extracted wall structure are shown in figure 6(b). As the figure shows, the extracted wall structures are labeled with different colors. The partially automatically generated BIM model is presented in figure 6(c). It can be seen from the figure that the material of the walls in the BIM model and in reality is not identical. The reason is that the model is only in Level of Development (LOD) 3, where the quantity, size, shape, location, and orientation are represented in the model element. Therefore, the used material is not considered. As can be seen from figure 6(d), the measurement results for the wall number 2 are visualized in the model. The presented color shows the contamination risk. The redder the color shows, the greater the possibility of the contamination will be.

To evaluate the proposed algorithm for the extracted building infrastructure. The precision and recall evaluation criterion [24] is used. Precision and recall is a widely used method for quality evaluation in pattern recognition and classification. The value of precision and recall are calculated as equations (1) and (2). Generally, the quality assessment is executed on a point level, where TP, FP, FN are the numbers of true-positive, false-positive, and false-negative points.

$$Precision = TP / (TP + FP) \quad (1)$$

$$Recall = TP / (TP + FN) \quad (2)$$

Table 1: Point classification evaluation of walls segmentation

Wall-segmentation	TP	FP	FN	Precision	Recall
-	461487	365	12239	0.999	0.97

The evaluated results of each detected wall structures are summarized in table 1 to table 3. Table 1 shows the evaluation of segmented wall structures from the point cloud. Overall, high values of precision and recall are observed (99.9% precision and 97% recall). As can be seen from figure 6(b), not all wall structures are detected through the proposed method. Therefore, the value of recall is

a bit lower. The evaluation of precision and recall at each reconstructed wall are collected in table 2. The results of reconstructed walls show a similar distribution from table 1. Furthermore, the accuracy of length from each wall are shown in table 3. Although the performance of different wall structures in precision and recall is different, the accuracy of wall detection is 95.4% on average. Overall, these results indicate that the developed method has high reliability.

Table 2: Point classification evaluation of reconstructed walls

Number	1	2	3	4	5	6	7	8	9	10
TP	47878	92222	4501	47630	27741	27654	8975	40475	109644	50365
FP	2293	1699	427	820	1509	62	998	857	2285	2043
FN	416	79	336	70	1993	3457	1445	2535	1422	11
Precision	0.954	0.98	0.91	0.98	0.95	0.998	0.89	0.98	0.98	0.96
Recall	0.99	0.999	0.93	0.999	0.93	0.89	0.95	0.94	0.99	0.99

Table 3: Accuracy of reconstructed walls

Number	1	2	3	4	5	6	7	8	9	10
Length in model(m)	2.3	5.99	2.2	4.77	2.5	1.75	0.66	2.72	9.75	1.26
Length in ground truth(m)	4.5	6	2.3	4.5	2.8	1.6	0.7	2.8	9.5	1.3
Accuracy	0.96	0.98	0.95	0.99	0.89	0.914	0.94	0.97	0.98	0.97

5 Conclusion and Outlook

The main goal of this paper is to develop a suitable algorithm to transform the point cloud data generated from the robotic system into a BIM model. After building the model, the measurement results of radiation can also be integrated into the BIM model on the surface of the wall element.

In order to achieve this purpose, an algorithm for extracting the feature information of the building structure from point cloud data was developed. Instead of using the RANSAC algorithm, a more efficient method is developed. The principle of the algorithm is a non-parametric approach and maximum likelihood estimation. For efficiently establishing the BIM Model, the visual programming language Dynamo is used, so that the wall structures can be built within minutes. Furthermore, the measurement results of radiation are integrated for visualization.

The results from the use case indicated that the developed algorithm has the ability to extract the building wall structure and then transform the extracted information into a BIM model with high accuracy. Although not all wall structures can be detected. One reason could be the poor quality of the point cloud, which means that not all structures are scanned in the point cloud. Another reason is that the randomly distributed wall structure can not be detected, which is a limitation of this method. Another limitation is that it could be restricted to geometries following the Manhattan world assumption. Furthermore, this is the first study reporting a method to integrate the radiation measurement in the BIM model. Since it is only the first step for the building reconstruction with a lower LOD level, the positions and geometries of windows as well as doors are out of consideration in this paper. Therefore, one possibility of the future work is to further develop the existed algorithm, so that the building constructions with a higher LOD level can be reconstructed in the BIM model.

6 Acknowledgment

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