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Point Cloud Segmentation Method Considering Wall Finishing Information Using 2D Material Segmentation and Back Projection

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Abstract: Progress monitoring and quality control using as-built Building Information Modeling (BIM) are actively applied to construction industry. In order to effectively perform these management works, Scan-to-BIM is a key process to create as-built BIM models. In the Scan-to-BIM process point cloud segmentation is a critical task to identify object semantic information from point cloud data. While segmentation methods of main structural components such as walls, slabs, columns, and ceilings are actively studied and used for the management works, segmentation considering the finishing works of these components is still challenging. Therefore, this study proposed a point cloud segmentation method that considered wall finishing information, utilizing both point clouds and 2D images acquired from terrestrial laser scanners. The proposed method is composed of three main steps: 1) Segmenting as-built point clouds of main structural components through the comparison with as-planned BIM. 2) Applying a SegFormer material segmentation model that trained with wall finishing data (2D images) from terrestrial laser scanners to segment wall finishing information in 2D images. 3) Labelling the point cloud with recognized wall finishing information using back projection based on camera pose data. The proposed method is expected to contribute to the enchantment of the level of details (LoD) in as-built BIM and be useful in progress monitoring and quality control of finishing works.

Key words: Scan-to-BIM, point cloud, segmentation, wall finishing, material segmentation

1. INTRODUCTION

Scan-to-BIM is a progressive method that generates as-built BIM based on point clouds, and it has been increasingly applied in construction management for progress monitoring and quality control [1–3]. The Scan-to-BIM process is typically composed into the following sequential stages: point cloud acquisition, point cloud preprocessing, point cloud semantic segmentation, and BIM modeling [3].

During point cloud acquisition, it is common to employ Terrestrial Laser Scanners (TLS) or utilize photogrammetry-based point cloud collection method. In the point cloud preprocessing stage, measures such as applying down-sampling to lighten the point cloud data [4] or procedures to eliminate noise data [5] are undertaken. Subsequently, in the point cloud semantic segmentation stage, main components are segmented by either leveraging as-planned BIM [6–9], utilizing 3D semantic segmentation deep learning models [10–13], or other approaches, and the preprocessed point cloud is segmented according to main components semantic classes. Then, the procedure concludes with BIM modeling conducted automatically or semi-automatically using tools such as Dynamo programming [14] or IFC code [15], resulting in the as-built BIM which is the final product of Scan-to-BIM.

Particularly, point cloud semantic segmentation is a critical task that determines the Level of Details (LoD) of the as-built BIM. The semantic classes considered in point cloud semantic segmentation task are connected to BIM modeling objects; it represents the LoD of the as-built BIM. On the other hand, most research related to Scan-to-BIM concentrates on the semantic segmentation of main components. Therefore, for improving LoD of as-built BIM, it is necessary to reflect finishing information in as-built BIM, should be considered in point cloud semantic segmentation task.

However, it is challenging to identify finishing information with conventional point cloud segmentation methods. To identify finishing information, As-planned BIM based methods require highly accurate registration between the as-built point cloud and the as-planned BIM. On the other hand, 3D semantic segmentation model based methods extract features based on 3D coordinates. Therefore, these models have limitations in detecting wall finishing with similar geometric characteristics.

To overcome the limitations, this study proposes a point cloud segmentation method that considers wall finishing information. The proposed method used point clouds and 2D images obtained from terrestrial laser scanners. First, as-built point clouds segmented into main components level using as-planned BIM. Subsequently, projection matrix was calculated based on camera pose data, matching point clouds and images, and applied SegFormer image segmentation model [16] trained with wall finishing image data. Then, the segmented finishing information labelled onto the as-built point clouds that labelled as the wall through back-projection. Finally, radius-based post-processing was applied to enhance the performance of labelling.

The proposed method is anticipated to contribute to the enhancement of the LoD in as-built BIM generated through Scan-to-BIM. Furthermore, it is expected to apply in research related to progress monitoring and quality control based on point clouds and as-built BIM.

2. LITERATURE REVIEW

In this section, the authors describe a literatures review related to point cloud semantic segmentation in the construction area. Most researchers have adopted various approaches for point cloud semantic segmentation, such as using as-planned BIM and adopting 3D semantic segmentation deep learning models.

As-planned BIM based point cloud semantic segmentation methods [6–9] typically involve registration and comparing the acquired point cloud with the as-planned BIM. These studies involving as-planned BIM for point cloud semantic segmentation have been analyzed to be applicable for identifying main components. However, these methods have limitation to address finishing information, since it requires high precise registration with as-planned BIM and as-built point cloud and high LoD of as-planned BIM.

Recently, the development of numerous 3D semantic segmentation deep learning models, such as PointNet[10], PointNet++[11], RandLA-Net[12], and DGCNN[13], has led to their application in the construction research area for Scan-to-BIM purposes[17–19]. While these studies successfully perform semantic segmentation of main components, they do not consider finishing information. In order to identify finishing information of main components, additional features such as texture, color, or material properties, beyond just 3D coordinates, must be considered. For instance, in the case of wall finishing, insulation walls, plasterboard walls, and concrete walls share similar geometric characteristics, making it challenging to differentiate them based on only 3D coordinates.

Some studies related to point cloud semantic segmentation or point cloud-based progress monitoring have considered the finishing information of objects. Dimitrov and Golparvar-Fard [20] proposed a method using material classification to apply in progress monitoring. Additionally, Han and Golparvar-Fard [21] performed 3D reconstruction through registration using both as-planned BIM and as-built point clouds for 3D reconstruction. Point clouds were acquired using Structure from Motion (SfM) and

Multi-View Stereo (MVS), then determined the finishing status of the progress by performing material classification based on Support Vector Machine (SVM) from images. Saovana et al. [22] acquired point clouds using SfM and applied an image-based instance segmentation model to perform point cloud semantic segmentation. These studies demonstrate the potential of using image-based material classification or segmentation results for point cloud semantic segmentation. However, their research focuses on representing the progress status based on as-planned BIM, making it difficult to derive point cloud-based BIM modeling parameters (such as vertices, level, center line, etc.) that are necessary for the automatic generation of precise and high LoD as-built BIM.

The studies by Park et al. [23] and Kim et al. [14] applied PointNet for point cloud semantic segmentation within operational buildings and applied material classification to panorama images captured by 3D laser scanners. However, the material classification showed low performance due to the distortion in panorama images, which needs improvement. These limitations underscore the necessity for refining both the segmentation accuracy and the material classification methodology to ensure the precision and high LoD of as-built BIM models.

3. METHOD

3.1. Overview

This research proposed a point cloud semantic segmentation method that considered wall finishing information. The method was developed following the pipeline shown in Figure 1 and could be outlined as follows: (1) A benchmark point cloud was generated from the as-planned BIM, artificially created by sampling from the surface of the BIM objects. This benchmark point cloud included main components information. The as-built point cloud, obtained from the 3D laser scanner, was down-sampled to reduce computing costs. (2) The preprocessed as-built point cloud was registered with the benchmark point cloud based on a target. After registration, a K-Nearest-Neighbors (KNN) search was performed on the benchmark point cloud, with the as-built cloud serving as the core point. The labels for main components of the core point were identified based on the search results. (3) The projection matrix was calculated based on camera pose data. The point clouds, segmented as walls, were projected onto the images. (4) To identify wall finishing information, the SegFormer image segmentation model, trained with five classes (concrete, insulation, plasterboard, masonry, opening) was applied. (5) The segmented results from SegFormer were labeled onto the points projected from the point clouds. Lastly, post-processing was applied to enhance the labeling results of the finishing information.

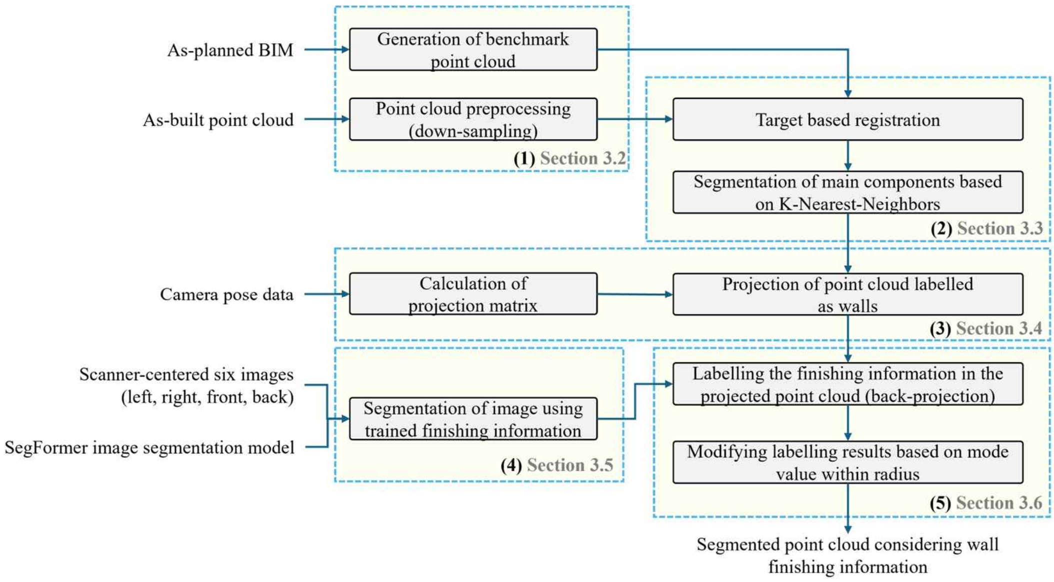

Figure 1. Proposed method workflow

3.2. Data acquisition and preprocessing

The proposed method utilizes the 'X7 scanner' developed by Trimble. This scanner is capable of capturing point clouds along with omnidirectional images (left, right, front, back, bottom, top), and the camera pose data for each image can also be acquired through Realworks, the software associated with the scanner. The method uses the four images (left, right, front, back) that capture the surfaces of walls, and the camera pose data is utilized to generate the projection matrix.

The method actively employs as-planned BIM, created based on CAD data from an actual apartment construction site, which was used for the development and experimentation of the method. Given the progress status of the site at the time of data acquisition, the as-planned BIM includes main components such as walls, columns, floors, and ceilings. The as-planned BIM, generated using Revit software, can be exported in OBJ format. The as-planned BIM, generated using Revit software, can be exported in OBJ format. This OBJ data was imported into Cloudcompare, an open-source software for point cloud and mesh data processing. This process enables the artificial generation of a point cloud from the surfaces of each components. In this paper, the artificially created point cloud extracted from the as-planned BIM is defined as the benchmark point cloud.

The point cloud acquired from 3D laser scanners typically contains an excessively large number of points, so appropriate down-sampling is commonly applied. The as-built point cloud is down-sampled with an interval of 0.05m, and the benchmark point cloud is also generated based on a 0.05m interval. Such preprocessing of the point cloud contributes to the improvement of the accuracy of the registration by inducing a similar density between the two point clouds. Additionally, overall computing costs can be reduced through down-sampling.

3.3. Segmentation of main components using K-Nearest-Neighbors

To perform segmentation of the main components of the as-built point cloud using the benchmark point cloud, it is necessary to closely align the two point clouds. The proposed method used target based registration for obtain high accurate registration results. Subsequently, the proposed method searched K-nearest points from the adjacent benchmark point cloud using KNN. The K value was set to 7, considering the down-sampling interval of 0.05m and the joints where main components intersect. The extracted seven points included main components labels, since they were part of the benchmark point cloud. The proposed method identified the main component label for the core points by adopting a mode label of the seven main components labels, thereby segmenting the as-built point cloud. Moreover, considering noise points captured from indoor clutter objects, if three or more out of the seven extracted points were located more than 0.2m from the core point, then that core point was separately classified as noise data.

3.4. Extraction of projection matrix for matching point cloud and images

The proposed method extracted mask images containing only wall information from four images to be used as inputs for the SegFormer image segmentation model. To achieve this, it is necessary to calculate the projection matrix that connected the point cloud and the images. The obtained projection matrix was used to project the point cloud, labeled as wall main components, onto images. It was also utilized for back-projection to label the wall's finishing information identified by the SegFormer image segmentation model onto the point cloud. The concept of calculating the projection matrix (P) is as shown in Figure 2.

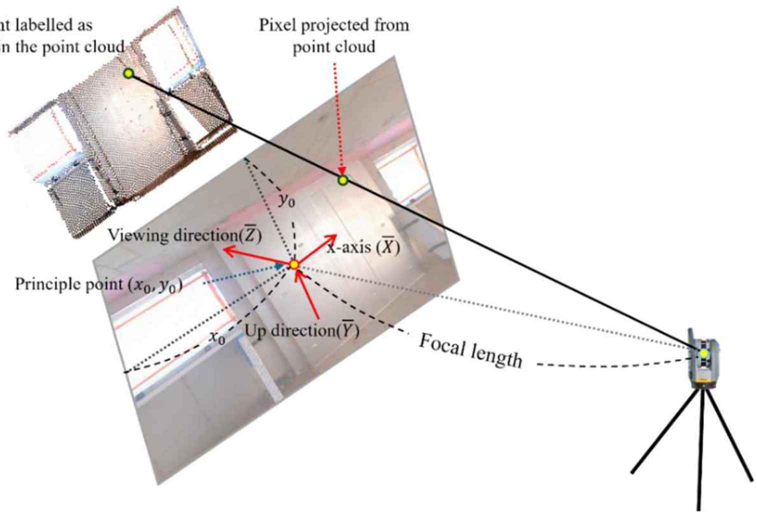

Figure 2. The concept of the projection matrix and matching between the point clouds and images

In this study, the calculation of the projection matrix employed the principles of rigid body transformation and homogeneous coordinates. The projection matrix (P) was defined by Equation (1).

$$P = K[R \mid T] \tag{1}$$

K is the matrix of intrinsic parameters calculated based on the focal lengths (f_x, f_y) and the principal point (x_0, y_0), as defined in Equation (2). Utilized 3D laser scanners was set to 1748x1748 pixels, and filed of view in both the width and height was fixed at 90°, it is established that f_x equals f_y.

$$K = \begin{bmatrix} f_x & 0 & x_0 \\ 0 & f_y & y_0 \\ 0 & 0 & 1 \end{bmatrix} \tag{2}$$

The information on camera position, viewing direction, and up direction is included in the extracted camera pose data, and this information can be utilized to calculate the rotation matrix (R). It is assumed that the point cloud exists in the coordinates of the world coordinate system. The rotation matrix (R) is defined as shown in Equation (3). The unit vector of the viewing direction is set as the z-axis ($\overline{Z}$), representing the direction the camera is facing, and the unit vector of the up direction is set as the x-axis ($\overline{X}$), representing the direction the camera is pointing upwards. The vector for the y-axis (Y) can be calculated through the cross product of the two established unit vectors.

$$R = \left[\overline{X}\,\overline{Y}\,\overline{Z}\right] \tag{3}$$

To calculate the projection matrix (P) defined in Equation (1), a translation vector (T) is required in addition to the rotation matrix. Meanwhile, the 3D laser scanner used in the proposed method captures both the point cloud and the image from the same location simultaneously. Therefore, by simply shifting the point cloud acquired at each scan station to have the scanner's location as the origin, the translation vector (T) can be defined as (0,0,0). Consequently, the projection matrix (P) needed for the proposed method can be defined as a 4x4 matrix in Equation (4).

$$P = \begin{bmatrix} R & 0 \\ 0 & 1 \end{bmatrix} \tag{4}$$

3.5. Segmentation of finishing information using SegFormer image segmentation model

The SegFormer image segmentation model was adopted to segment images into finishing information classes. The SegFormer used in this study leveraged a model provided by the Pytorch library, with transfer learning applied to train the model on four classes: concrete, insulation, plasterboard, masonry and opening. The training data consisted of images directly acquired by the authors from an apartment construction site, and the dataset was organized as indicated in Table 1. The training results achieved 0.93 mean accuracy about the test dataset.

Table 1. Details of training, validation, and testing datasets for generation the SegFormer image segmentation model applied in this study

Index	Concrete	Insulation	Plasterboard	Masonry	Opening
Train	944	717	769	762	730
Valid	242	210	168	223	229
Test	168	107	89	1310	101
Total	1,354	1,034	1,026	1,115	1,060

The proposed method applied image preprocessing task to enhance segmentation results. Particularly, some part of insulations in images, captured as high brightness due to high reflectiveness of surface. To address this issue, the Contrast Limited Adaptive Histogram Equalization (CLAHE) was adopted before being used as input to SegFormer. Additionally, while the trained images are 640x640, the size of images acquired from a 3D laser scanner is 1748x1748. Therefore, to perform appropriate segmentation, the input image of 1748x1748 was divided into four patches, and each was segmented using SegFormer.

3.6. Labelling wall finishing information using back-projection and post-processing

According to the projection process (Section 3.4), the projected point clouds have two-dimensional coordinates on images. Therefore, the finishing information of projected point clouds was easily defined by following the segmentation results of each pixel. However, in the results of SegFormer, various classes were scattered on the walls due to incomplete segmentation. Therefore, post-processing is required to obtain more accurate results. To address this issue, the proposed method applied radius search-based post-processing. First, all points search for the nearest points within a 0.5m radius. Second, they obtained the most common values of finishing information within the searched points. Lastly, the core point's finishing label was modified to the mode value obtained in the second step. The proposed method performed abovementioned process twice. Finally, the proposed method was able to obtain a segmented point cloud that incorporates wall finishing information.

4. EXPERIMENT AND RESULTS

4.1. Experiment data

To validate the proposed method, point clouds and images acquired from an actual apartment construction site were utilized. The proposed method necessitates data such as as-built point clouds, images, and as-planned BIM. Figure 3 shown the data employed in the experiment; Figure 3(a) illustrates the as-planned BIM, Figure 3(b) displays the as-built point cloud, and Figure 3(c) provides an example of the six images captured at the first scan station. The ceiling was excluded from Figure 3(a) and Figure 3(b) to allow for proper visualization of the interior space.

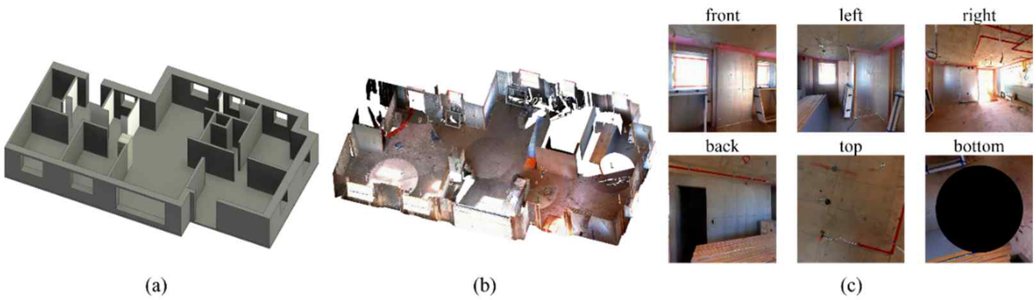

Figure 3. Experiment data (a): as-planned BIM, (b): as-built point cloud, (c) captured images at the first scan station.

4.2. Results

The experimental results for validating the proposed method were carried out as follows: (1) measuring the accuracy of the semantic segmentation of main components based on ground truth, and (2) measuring the accuracy of finishing information labeling for walls, also based on ground truth. Walls at the experiment site contained just concrete and insulations. For validation in (2), it classified classes into concrete and insulation detailing their performance values.

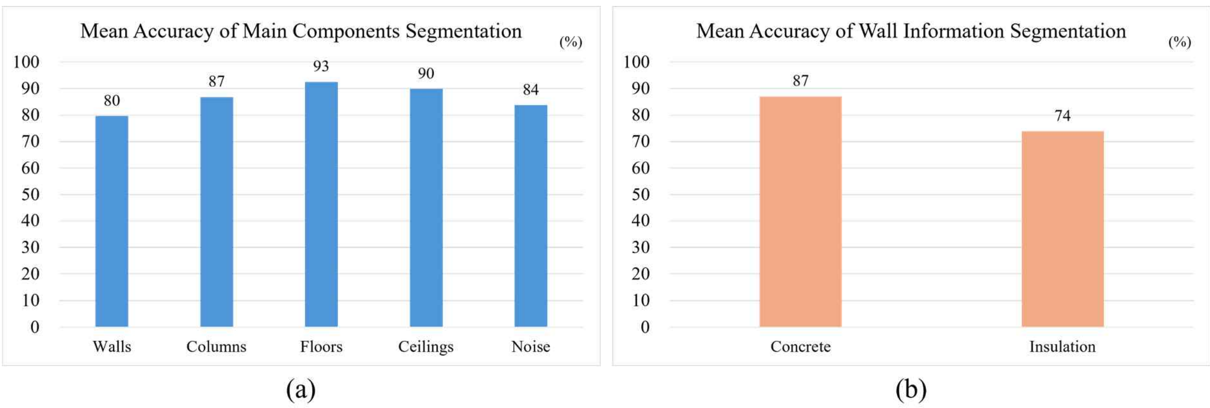

Figure 4. experimental results (a): confusion matrix of main components segmentation, (b): confusion matrix of wall finishing information labelling.

As shown in Figure 4(a), the proposed method demonstrated segmentation accuracy for main components with walls at 80%, columns at 87%, floors at 93%, ceilings at 90%, and noise at 84%. The mean accuracy was calculated to be 85.9%. Analyzing the accuracy for individual main components, the segmentation of floors and ceilings showed high performance with 92.53% and 89.75%, respectively. Columns showed a respectable performance with an accuracy of 86.81%, while noise had a lower performance at 83.68%. This is related to the lower segmentation performance of walls, which showed a lower accuracy of 79.62%. This is analyzed to be due to the influence of noise data, such as construction materials, being placed adjacent to the walls. Furthermore, incorrect segmentation caused by progress gaps between as-planned BIM and as-built point cloud also had an impact on performance degradation.

As shown in Figure 4(b), the proposed method demonstrated segmentation accuracy for wall finishing information with concrete at 87% and insulation at 74%. As the results, it was found that the performance for identifying insulations was relatively low. A review of the input images revealed that incorrect segmentation results were primarily produced in areas where light flares occurred on the highly reflective surfaces of insulations. These areas contributed to the comparatively lower segmentation performance. Additionally, the difference in image size between the trained image and the input image caused scale issues. The authors believe that addressing the size discrepancy between training and input images during the training step, along with incorporating a more diverse dataset, will enhance the performance of SegFormer and final labelling results.

5. CONCLUSIONS

In this study, we considered the finishing information of walls in point cloud segmentation. The proposed method utilizes point clouds, images, and camera pose data acquired from a 3D laser scanner. The main steps include: 1) Segmenting the as-built point cloud to the main components level using a benchmark point cloud artificially generated from the as-planned BIM. 2) Creating a projection matrix using camera pose data and projecting only the point clouds segmented as walls onto images. 3) Each image is segmented into finishing information classes using SegFormer, and the segmented results are back-projected. The proposed method achieved an accuracy of 85.9% for segmenting main components and 80.5% for labeling wall finishing information.

The proposed method has demonstrated the feasibility of identifying finishing information using images and its application to point clouds. Future research will focus on improving the performance of segmenting main components using as-planned BIM. Additionally, we plan to enhance the labeling performance of finishing information by adjusting the image size trained in SegFormer and improving post-processing. The proposed method is expected to contribute to enhancing the Level of Details (LoD) of as-built BIM generated through Scan-to-BIM.

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