Semantic As-built 3D Modeling of Buildings under Construction from Laser-scan Data Based on Local Convexity without an As-planned Model

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ABSTRACT

As-built building information models (BIMs) need to be represented with the composing building elements having their own functional semantic information. In order to generate such as-built BIMs with composing building elements, it is necessary to recognize each of the semantic elements and separate them from each other. In addition, the as-built BIM needs to be generated and updated during or after each major construction activity because most of the structural elements and nonstructural elements (especially for mechanical, electrical, and plumbing (MEP) components) are covered by other objects as the construction phase progresses. This study aims to propose a method for generating a semantic as-built BIM from laser-scan data acquired during the construction phase, especially for structural works. A field experiment was performed to validate the proposed method by acquiring and processing laser-scan data from the construction site. The experimental result shows that the proposed method can be used for semantic as-built BIMs without any prior information from as-planned models.

Keywords – As-built BIM, BIM, Laser-scan Data, Scan-to-BIM, Structural Works

1 Introduction

As-built building information models (BIMs) need to be represented with the composing building elements having their own functional semantics [1–4]. Building elements consist of structural and nonstructural elements. Structural elements include foundations, floors, columns, walls, girders, beams, and slabs, and nonstructural elements include mechanical, electrical, and plumbing (MEP) components (mechanical equipment, piping, duct work, and electrical equipment), architectural components (such as exterior walls, interior partitions, ceilings, canopies, stairways, and freestanding walls), and other finishes (doors and windows). All of the building elements are connected and networked with each other to realize their functions. For example, a girder is supported by two or more columns. For this reason, in order to generate an as-built BIM with the composing building elements, it is necessary to recognize each of the semantic elements and separate them from each other. In addition, these building elements are constructed as planned work tasks during the construction phase. As the construction phase progresses, most of the structural elements and nonstructural elements (especially for MEP components) are covered by other objects, such as architectural components and other finishes, which are installed later. For this reason, in order to generate an as-built BIM with the composing building elements, it needs to be generated and updated during or after each of the major construction activities, such as structural, MEP, architectural, and finish works for use in project management purposes.

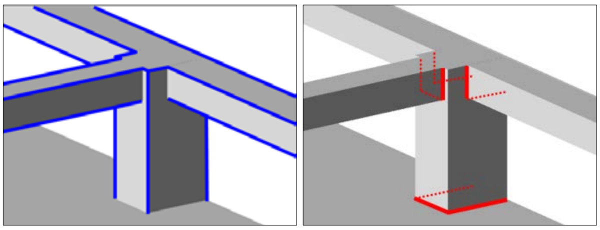
Few research studies have been conducted to propose methods for recognizing semantic elements in buildings during the construction phase [5–11] as well as during occupancy [1,2,4,12,13]. These research studies performed as-built data acquisition using spatial survey technologies that are based on photogrammetry [8] and laser scanning [5,6,1,7,9,2,4,12,13]. From the acquired as-built data represented in the point cloud format, research studies that focused on the construction phase proposed methods to recognize and model the structural elements by utilizing the as-planned model [5–9]. However, such a scan-to-BIM approach can be generally not effective where discrepancies are observed in the as-built and as-planned conditions. Such discrepancies are due to construction errors (human errors) and changes related to constructability issues made in the field. Although a recent study by Bosché et al. [10,11] tackled this problem by integrating scan-versus-BIM and scan-to-BIM approaches for as-built modeling of MEP work, this method also primarily depends on the as-planned model.

Research studies that focused on the occupancy phase have shown that the structural elements that are exposed, as well as architectural elements, can be recognized and/or modeled [1,2,4,12,13]. However, such methods are applicable to planar and non-volumetric elements, such as walls, doors, and roofs in an outdoor environment and walls, floors, ceilings, windows, and doorways in an indoor environment, because these methods are basically based on the plane extraction process. In other words, these methods require additional processes to recognize volumetric elements that consist of several planes or even nonplanar surfaces, such as columns, girders, beams, and MEP components. For example, in order to recognize a column, additional processes of finding a few different planes comprising the column and combining them into a unified entity are necessary [14,15]. In summary, to our knowledge, there are limited methods available to generate a semantic as-built 3D BIM during the construction phase without an as-planned model.

The ultimate goal of this study is to develop a method for generating and updating as-built BIMs during or after each of the major construction activities, such as structural, MEP, architectural, and finish works, for use in project management purposes. To achieve this goal, this study aims to propose a method for generating semantic as-built BIMs from laser-scan data acquired during the construction phase, especially for structural works. This paper is organized as follows: Section 2 provides an overview of the proposed method and basic principles. Section 3 provides an explanation of the methodology. Section 4 provides the results of field experiments. Finally, Section 5 provides a summary and recommendations for future research.

2 Overview of the Proposed Method and Basic Principles

This study proposes a method for scene segmentation, a process of partitioning laser-scan data acquired during the construction phase into meaningful parts that consist of different types of building elements, for example, floors, columns, walls, girders, beams, and slabs. The main idea is that most objects are themselves composed of connected and enclosed convex surfaces and are separated from other objects by concave boundaries [16]. From this point, each of the structural elements can be recognized by merging areas having convex properties enclosed by concave boundaries. Convex and concave properties can be simply differentiated as follows. Two adjacent surfaces of an object have a convex property (see Figure 1(a)). On the other hand, two adjacent surfaces of different objects have a concave property (see Figure 1(b)). Such convex and concave properties are proven as unique and powerful features for scene segmentation from 3D point clouds [17,16].



(a) (b)

Figure 1. (a) Convex areas (in blue); (b) Concave areas (in red)

Figure 2 illustrates the main steps of the proposed method. The proposed method is initiated by the region-of-interest (ROI) detection process. The laser-scan data acquired during the construction phase contains building elements to be modeled as well as other objects, such as stacked materials. For this reason, the first process is proposed to distinguish 3D points of corresponding building elements to be modeled, such as structural elements. Then, the process is followed by scene approximation using an adjacency graph, which utilizes spatially connected surface patches. In the adjacency graph, the convex and concave properties of the edges are computed based on a local criterion. Then, locally connected subgraphs with convex properties are identified through the region-growing process, which represents building elements. The details of the proposed method are as follows.

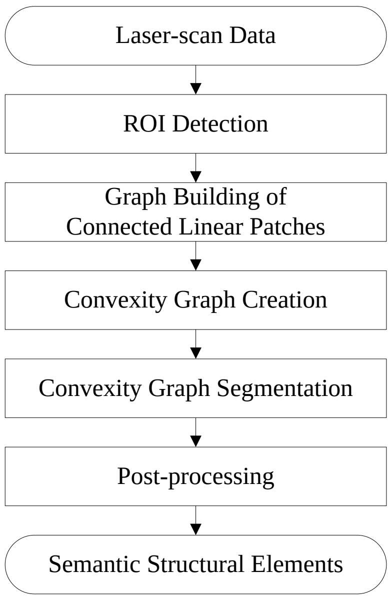


Figure 2. Proposed method for semantic as-built BIM

3 Methodology

3.1 Region-of-Interest (ROI) Detection

The laser-scan data acquired during the construction phase comprise 3D points' coordinates (x, y, z) and the (R, G, B) color values of the corresponding 3D points. In order to distinguish 3D points of the corresponding building elements to be modeled, structural elements in this case, an ensemble classifier proposed by Son et al. [18] was employed. This method uses a color value as a feature to distinguish ROI from laser-scan data. The ensemble classifier uses a voting scheme that internally makes use of base classifiers (support vector machine, C4.5, and k-nearest neighbors) and combines them in an effort to produce better results. By applying the ensemble classifier, 3D points corresponding to the structural elements comprising construction materials such as concrete, steel, or wood are classified.

3.2 Graph Building of Connected Linear Patches

After the ROI detection is completed, 3D points' coordinates (x, y, z) are used to segment the resulting data into semantic parts that consist of different types of building elements. As the first step, a graph of connected linear patches is generated. This step is based on the supervoxel algorithm proposed by Papon et al. [19]. The supervoxel algorithm is designed for edge-preserving segmentation where each of the supervoxels in an adjacency graph is regarded as a linear patch, and their normal vectors are computed. Here, a normal vector is defined as the facing outward following the right-hand rule, which means the vertices comprising each faces are arranged counter-clockwise. This approach specifies the normal vector to be unique.

The supervoxel algorithm has advantages of efficiently processing the huge 3D point cloud by achieving substantial data reduction [16]. By employing this algorithm, the adjacency graph is built from the ROI detection result, that is, neighboring voxels are those that share a face, edge, or vertex. This is computed within the octree structure by searching and determining the neighboring leaves in the voxel grid. Details of the supervoxel algorithm can be found in Papon et al. [19], Stein et al. [16], and Stein et al. [20].

3.3 Convexity Graph Creation

Once a graph of connected linear patches is built from the ROI detection result, a convexity graph is created by classifying edges of the graph of connected linear patches. Here, in order to determine whether a connection between patches has convex or concave properties, two criteria proposed by Stein et al. [16] are employed, that is, *convexity* and *sanity*.

The convexity is defined by an angle threshold in order to compensate for errors in the normal vector estimation. In addition, adjacent patches having small concave properties can be ignored by regarding connections between adjacent patches whose normal difference is less than the angle threshold as having a convex property. The sanity is defined in order to identify connections where adjacent patches are only connected in a singular point.

3.4 Convexity Graph Segmentation

From the created convexity graph, each of the elements connected by convex edges is found. This process considers the way elements are connected and also consequences of the connectivity between patches. Convexity graph segmentation is achieved by a region-growing process. By selecting arbitrary seed supervoxel, it starts region growing, which propagates the seed-patch to those patches having convex edges until a concave property is reached.

For the selected seed supervoxel and propagated supervoxels, segment label is assigned. Then, the region-growing process is started again with another seed supervoxel that has not been labeled. This process continues until segment llabels have been assigned to all supervoxels. Through this region-growing process, convex-connected patches are found around the concave edges. As a result, it leads to an enclosing concave boundary that segments the convexity graph.

3.5 Post-processing

In the resulting segmented 3D point cloud, small segments can be found at the edge. These are caused by normal vector estimation, which is based on the local neighborhood. As the first step of the post-processing, such small segments are discarded with filters as minimal segments. Here, simple filter using the pre-defined filter size is implemented. This filtering step repeated until no segments smaller than the filter size is present in the 3D point cloud.

As a result, each of the columns is segmented from the other structural elements. However, beams and girders need to be further segmented into each element because the bottoms of the connected beams and girders do not have concave properties. In order to separate each of the beams and girders, *connectivity* is used as a criterion. For example, a girder is attached to or supported by a column or a wall. A beam is attached to two adjacent girders. By using this connectivity criterion between the column and girder, each of the girders is segmented first, and then each of the remaining beams is clustered. Finally, over-segmented walls, floors, and slabs are merged again by considering their locations in 3D space.

4 Field Experiment

4.1 Experimental Setup

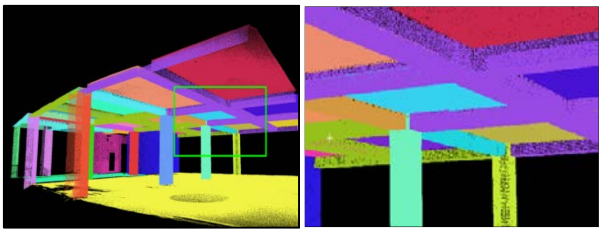
In order to evaluate the capability of the proposed method, as-built data were acquired during structural works using ScanStation C10 by Leica Geosystems, Ag. For this purpose, laser scanning was performed from 16 scan positions at the 1st floor of a new building construction project. Following laser scan data collection, all 16 scan point clouds were registered in a common coordinate system.

4.2 Results and Discussion

Figure 3 shows the result of the region-of-interest (ROI) detection from the registered 3D point cloud. In this case, 3D points corresponding to concrete structures were targeted and detected by employing the ensemble classifier proposed by Son et al. [18]. Through this process, the stacked materials and fence having different color values from the concrete structures, were distinguished and discarded. After the ROI detection, there were 2 floors (each of having different heights), 9 columns, 2 walls, 13 beams, 18 girders, and 2 slabs of having different heights.

Figure 3. Result of ROI detection

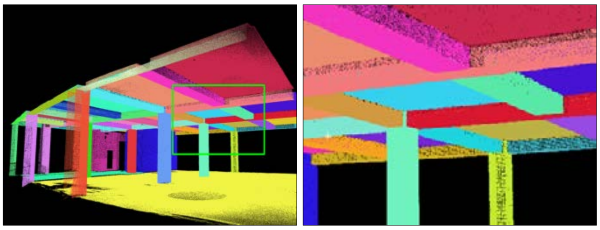
Figure 4 shows the result of the graph building of connected linear patches, convexity graph creation, convexity graph segmentation, and filtering processes. In this figure, different segments are displayed using different colors. This figure shows the proposed method based on the convexity and concavity properties, dividing the 3D point cloud between floors, columns, beams and girders, and slabs. The segmented elements are as follows: 3 floors, 9 columns, 2 walls, 3 beams, 6 girders, 5 beam-girder composites, and 21 slabs connected by walls, beams, and girders. Here, 5 beam-girder composites indicate that they are under-segmented, as the bottoms of the connected beams and girders do not have concave properties, and beams and girders are under-segmented, for example, the 3D points colored in purple. Therefore, post-processing was performed to separate each of the beams and girders using a *connectivity* property with adjacent columns and walls.



(a) (b)

Figure 4. (a) Result of convexity graph segmentation and filtering; (b) Magnified portion of (a)

Figure 5 shows the result of the segmentation between beams and girders. The 3D points colored in purple (see Figure 4) were segmented into different beams and girders, as shown in Figure 5. As a result, 5 beam-girder composites were re-segmented into 10 beams and 12 girders.



(a) (b)

Figure 5. (a) Result of the segmentation between beams and girders; (b) Magnified portion of (a)

Finally, the last step of the post-processing was performed on the result shown in Figure 5. As shown in Figures 4 and 5, floors and slabs were over-segmented. In the case of the floors, they were over-segmented because holes were produced since the stacked materials on the floors were distinguished and discarded in the ROI detection process. By merging the segments having similar height values, 3 floors were merged into 2 floors. In addition, in the case of the slabs, they were over-segmented because each part of the slabs was connected by adjacent walls, beams, and girders. By merging the segments having similar height values, 21 slabs were merged into 2 slabs (see Figure 6). As a result, a total of 45 structural elements were successfully segmented with respect to their own functional semantics.

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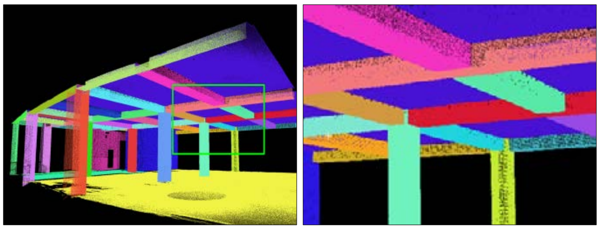

(a) (b)

Figure 6. (a) Final result of the proposed method; (b) Magnified portion of (a)

5 Conclusion

This study presented the method for scene segmentation, the process of partitioning laser-scan data acquired during the construction phase into meaningful parts that consist of different types of building elements, for example, floors, columns, walls, girders, beams, and slabs. By using local convex and concave properties of the structural elements, the proposed method segments the laser-scan data into semantic building elements. The capability of the proposed method was evaluated with the laser-scan data acquired through the field experiment. The experimental results showed that the proposed method could be used for semantic as-built BIM without any prior information from an as-planned model. In addition, computational efficiency was achieved by employing the supervoxel algorithm.

Future research will be devoted to the quantitative evaluation of the proposed method in various building environments. Moreover, the proposed method will be expanded to develop a method for generating and updating as-built BIM during or after each major construction activity—not only structural works but also MEP, architectural, and finish works—for use in project management purposes.

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