

Semi-automated approach to indoor mapping for 3D as-built building information modeling



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ABSTRACT

BIM (Building Information Modeling), chiefly in the form of a 3D “as built” model or information sharing platform, has emerged as a powerful solution to the dynamic requirements of AEC (Architecture, Engineering, and Construction). However, whereas fast and accurate reconstruction of building interiors is essential to any collaborative construction management process, manual creation and utilization of a 3D as built model typically results in low productivity and erroneous modeling results. This paper proposes a semi automated method that accounts for and resolves the major problems in the streamlined manual process of 3D as built model creation in BIM. The method generates a 3D wireframe model combined with clutter data, which is then imported into a BIM tool for as built modeling. The present study evaluates the proposed method by applying it to two typical rooms in a test building. The 3D as built model was then subjected to an accuracy assessment using reference points acquired by a total station. The contributions of the proposed method, as compared with fully manual operation, are: (1) reduction of the huge data size of the original point clouds; (2) improvement of the productivity of as built BIM creation with the aid of 3D wireframes; and (3) accuracy enhancement through a refinement process that entails segmentation and regularization. However, the proposed method is limited to building interiors consisting of planar structures; the modeling of detailed objects, such as windows and doors, unfortunately, still requires manual operation. Thus, further research on detail modeling and refinement is necessary in order to increase the method's automation and enhancement of its overall suitability for mapping complex indoor environments.

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1. Introduction

BIM (Building Information Modeling) has become a major, must have tool for construction and facility management in the AEC (Architecture, Engineering, and Construction) domain. BIM typically has been applied in preplanning, design, and construction and for integrated project delivery of buildings and infrastructure; recently, however, the research focus has been shifted from earlier building lifecycle stages to maintenance or refurbishment of existing build

ings. The 3D “as built” model, correspondingly, is now an essential means of accurately representing recently constructed buildings and their facilities to support maintenance process data. However, the numerous BIM implementations have predominately been for new buildings; BIM application to existing buildings is still relatively rare. In fact, as existing buildings often lack as built documentation due to a lack of refurbishment, BIM application limitations and research challenges with respect to such structures are expected (Volk, Stengel, & Schultmann, 2014). Generally, 3D as built BIM construction entails three main tasks: (1) geometric modeling, (2) object recognition, and (3) relationship modeling (Tang, Huber, Akinci, Lipman, & Lytle, 2010). The major focus in this paper is the improvement of 3D geometric modeling (hereafter: 3D modeling).

The creation of a 3D model, not to mention the mere acquisition of the necessary data and spatial measurements requisite for its creation, however, entails huge time and human resource demands. To accelerate the data acquisition process and improve the accuracy of spatial measurements, many commercial vendors and research groups have developed and utilized various sensor based surveying technologies (Aryicci, 2007; Furukawa, Curless,

Abbreviations: BIM, Building Information Modeling; AEC, Architecture, Engineering, and Construction; RANSAC, RANdom Sample Consensus; FOV, Field of View; RMSE, Root Mean Square Error; SAS, Spherical Accuracy Standard.

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Seitz, & Szeliski, 2009; Henry, Krainin, Herbst, Ren, & Fox, 2012; Kersten, Sternberg, & Stiemer, 2005; Sansoni, Trebeschi, & Docchio, 2009). In current practice, the 3D laser scanner, with its capacity for high speed collection of massive point clouds, is widely employed (Han, Cho, Kim, Jung, & Heo, 2012; Tang & Akinci, 2012; Volk et al., 2014).

However, the laser scanning of building interiors is complicated by small and complex spaces that, typically, are filled with a variety of clutter, such as moving objects, home appliances, furniture, and other accessories (Fig. 1). To handle such occluded areas, 3D laser scanners collect, from close distances and at multiple locations, huge point clouds that often incur system slow down or failure. There is a growing number of techniques and algorithms that aim at handling unlimited, massive 3D point clouds (Richter & Döllner, 2014), but 3D point cloud size is still a major issue for scalability in the case of large, complex indoor environments. Necessarily, the conventional 3D modeling process generally uses a point cloud reduced by 50–90%, which leads to loss of valuable data pertaining to details (Heo et al., 2013; Jung et al., 2014). Furthermore, relative to the mapping of exterior shapes, the inefficiency of 3D indoor mapping is due to enclosing point clouds depicting principal building components, such as the floor, ceiling, and walls. Clutter hampers modelers' identification of detailed building objects, such as windows and doors. A special function, such as a profile or cross section view, is required to identify building objects within the limited range of point clouds. In addition, occlusions caused by clutter represent lost information that requires modelers to subjectively determine building objects' shapes. This kind of manual 3D model creation, unfortunately, is highly subject to low productivity and erroneous modeling results.

To facilitate the 3D modeling process, a new, semi automatic method is proposed that can address the following major problems: (1) the huge size of point clouds, (2) the inefficiency of manual indoor modeling, and (3) the low mapping accuracy of 3D models. The remainder of this paper is organized as follows. Section 2 briefly reviews the literature on indoor as built BIM creation and its limitations. The proposed approach is fully described via subsection 3.1, subsection 3.2, subsection 3.3, subsection 3.4 and subsection 3.5. In Section 4, the performance of the proposed procedures is demonstrated with two experimental results. Finally, in the concluding Section 5, the strengths and limitations of the proposed method are discussed.

2. Related work

3D models have been widely employed in numerous urban system domain applications, such as urban planning, disaster man-

agement, navigation systems, and the mobile service industry (Mao, Harrie, & Ban, 2012; Over, Schilling, Neubauer, & Zipf, 2010). 3D representation can enhance understanding of complex spatial and functional relationships in the contemporary 3D city; thus, the demand for high complexity 3D urban modeling has increased, as driven by recent industry developments. Moreover, complex 3D city model requires not only the appearance of buildings, but also the indoor space. For example, a 3D city model specified at the LoD4 level of detail of CityGML contains a detailed description of both outdoor and indoor spaces, including architectural components (Xie, Zhu, Du, Xu, & Zhang, 2013; Zhao, Zhu, Du, Feng, & Zhang, 2012). Along with this trend, recent ubiquitous computing and navigation advances have specifically favored the application of BIM to indoor spaces. Accordingly, the range of application of 3D modeling has been progressively extended from outdoor to indoor environments. Nonetheless, as city models used in practice have focused on representation of the outdoor environment and building facades, their information provision with respect to indoor environments remains limited (Heo et al., 2013; Isikdag, Zlatanova, & Underwood, 2013; Li, Claramunt, & Ray, 2010).

In the AEC domain, a few fully automated reconstruction methods for the creation of 3D models from point clouds have recently been addressed. Arayici (2008) created 3D CAD models of existing structures using a semi automated technique entailing point cloud data acquisition, mesh model generation, and 3D CAD model creation. In response to the demand for automated as built modeling, Budroni and Böhm (2010) developed a volume sweep and cell decomposition method for the reconstruction of Manhattan world interior scenes from point clouds. The output is a 3D CAD model of indoor environments, but the key assumption is the absence of furniture or small objects. Valero, Adan, and Cerrada (2012) presented an automatic method that yields boundary representation models of indoor environments that contain a variety of clutter. However, they estimate structural lines of indoor environments by the intersection of two adjacent planes, which is not a mathematically rigorous approach. Furthermore, they do not provide detailed modeling of doors and windows. Xiong, Adan, Akinci, and Huber (2013) proposed a context based modeling method that produces a semantic 3D building interior models in the presence of clutter and occlusions. However, this method is restricted to simple rectangular surface modeling without consideration of as built BIM creation. Alternatively, Jung et al. (2014) proposed a semi automated method entailing RANSAC based geometric drawing generation followed by manual modeling in BIM software, by which a huge and complex indoor model can be generated. Unfortunately, some of the surface boundaries of such geometric drawings are,

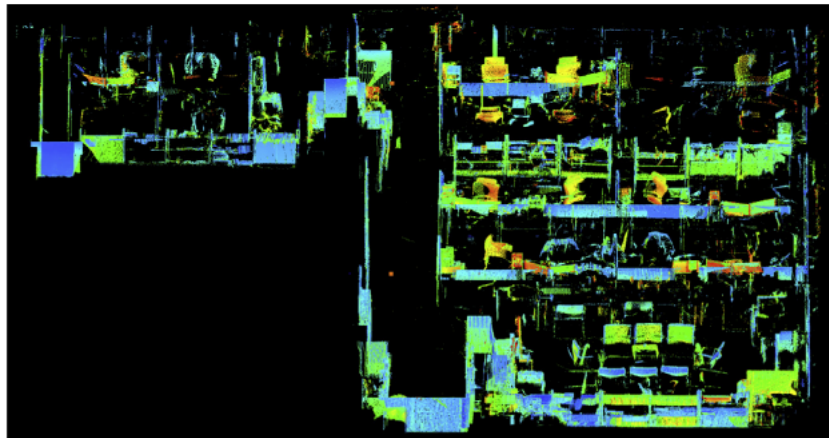


Fig. 1. Clutter shown in cross-section view for point clouds of the office.

due to the effect of noisy points, irregular zigzag shapes, which renders modeling of specific components, for example, curvilinear surfaces, difficult. The review of the relevant research indicates that manual operation remains unavoidable in modeling the details of building objects and ensuring accurate as built BIM results.

3. Methodology

3.1. Overview

The semi automated indoor mapping methodology proposed in this paper consists of four major steps: (1) point cloud preprocessing, (2) vertical modeling, (3) 2D floor boundary modeling, and (4) 3D as built modeling (Fig. 2). In the scanning of interiors, beams from LiDAR equipment penetrate transparent objects, such as windows, and some returns from building exteriors are included in point clouds. Elimination of noise data from buildings outside is assumed when point clouds are delivered at the initial stage of a modeling process. Vertical modeling, the second step, estimates ceiling to floor heights and filters noise data that is referred to as clutter data. In the third step, point clouds are projected onto the horizontal plane, and a 2D floor boundary is extracted with a tracing grid, followed by segmentation and regulation for refinement. In the fourth and final step, a 3D wireframe model is created by extruding the 2D floor boundary with the height estimates from the vertical modeling. In the 3D as built modeling process, noise data is considered an important source of additional detail, such

as the locations of light fixtures, doors, and window frames. Thus, a 3D wireframe model combined with clutter data is imported into BIM for “as built” modeling.

3.2. 2D pseudo point structure

In the preprocessing step, a 2D pseudo point structure, which characterizes the z value variations in interiors to be modeled, is proposed as the primary means of height modeling and point cloud filtering. Pseudo points at a predefined spacing interval are created with reference to the horizontal coordinates of the original points as follows:

$$\begin{aligned} X_{ps} &= \text{Round}(X_{pc}/SI) \times SI \\ Y_{ps} &= \text{Round}(Y_{pc}/SI) \times SI \end{aligned} \quad (1)$$

where X_{ps} , Y_{ps} : pseudo point coordinates, X_{pc} , Y_{pc} : original point coordinates and SI : horizontal spacing interval of pseudo points.

As shown in Fig. 3(a), the points from a laser scanner are combined and registered in a Cartesian coordinate system. In Fig. 3(b), the box threshold indicates the spacing interval between each pseudo point. The pseudo points (p_1 , p_2 , and p_3) are created according to all original points having the projected 2D locations within the box threshold, with which the z coordinates in the list of original points represent the height variations. Fig. 3(c) shows that each pseudo point stores the 3D coordinates of original points falling within the box threshold. The pseudo point is similar to the virtual grid in the sense that both of them divide the space in a regular

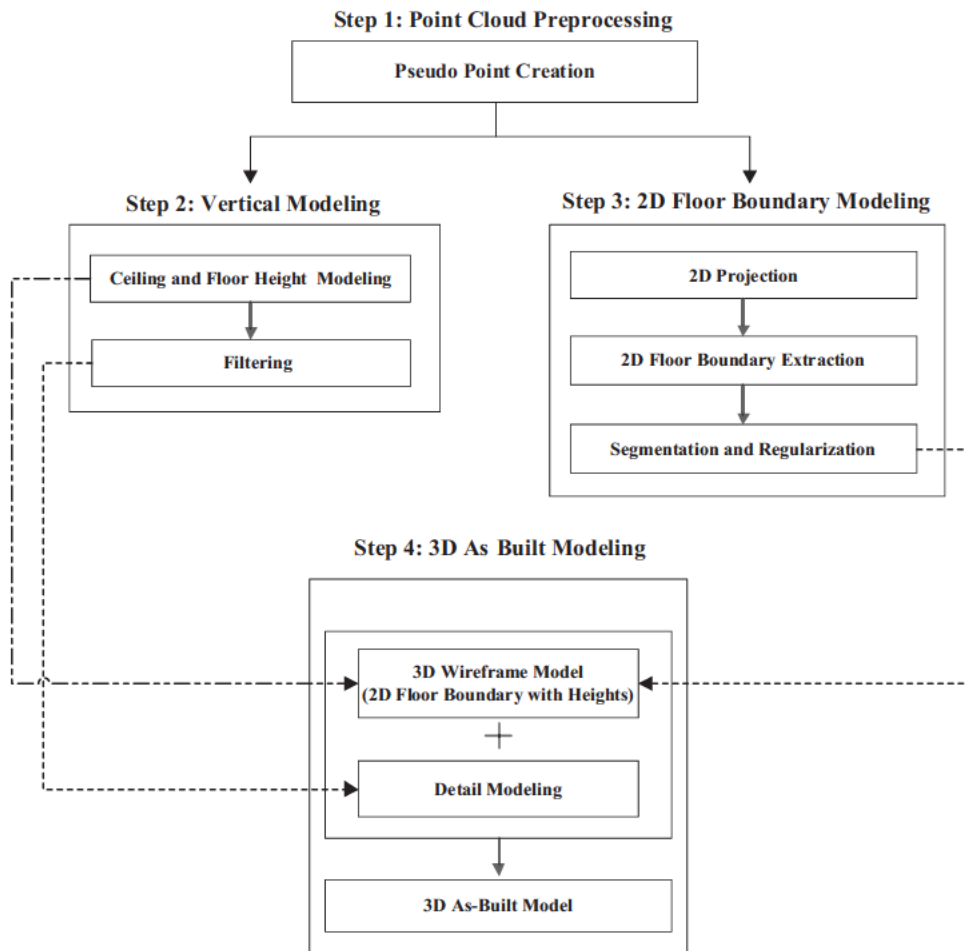


Fig. 2. Overall process of the proposed method.

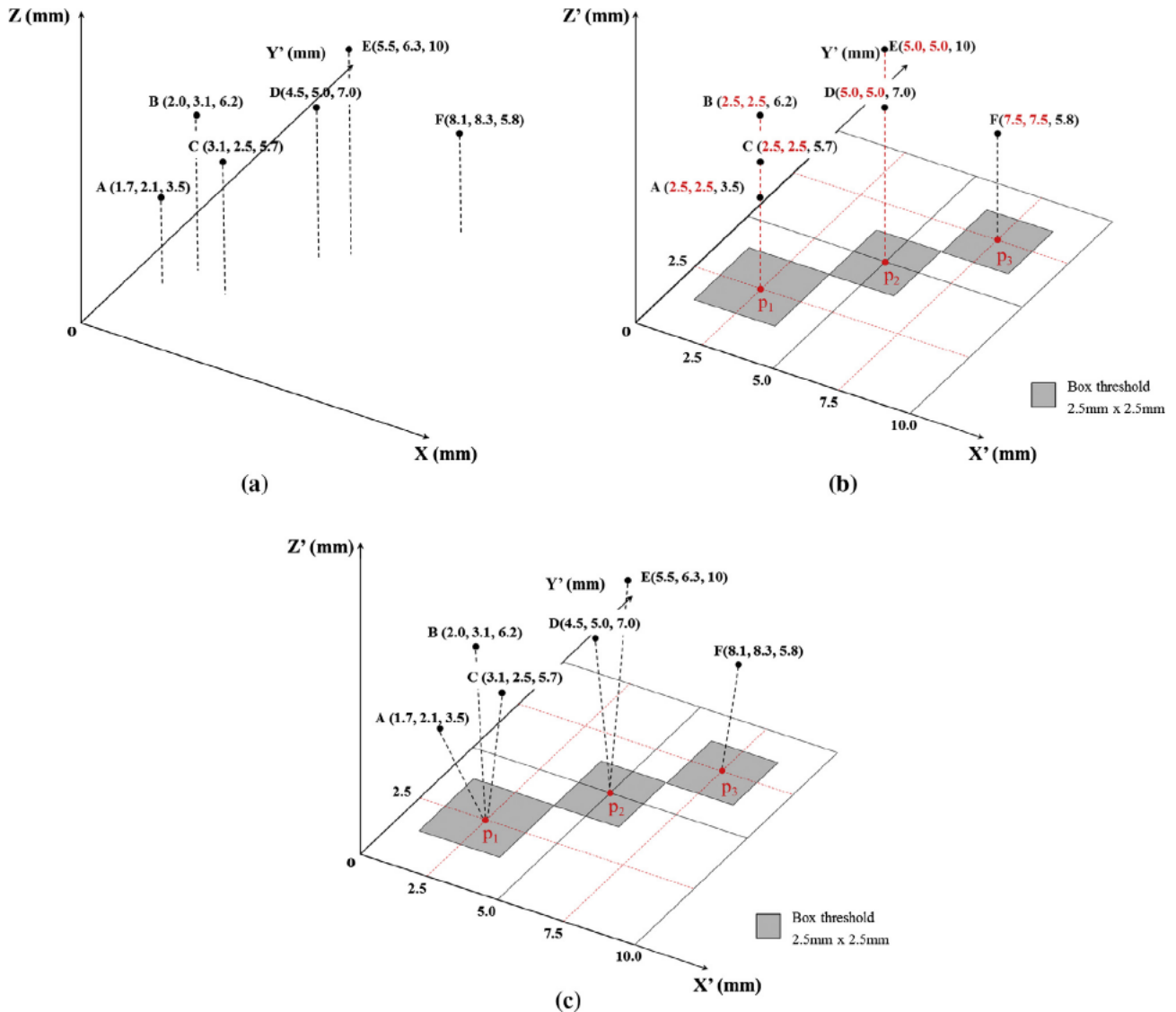


Fig. 3. Conceptual view of pseudo points: (a) original points referenced in the Cartesian coordinate system; (b) created pseudo points (p_1, p_2, p_3); (c) pseudo points associated with the original points.

interval (Han, Heo, Sohn, & Yu, 2009; Han et al., 2012). However, unlike the virtual grid, pseudo points are created only when original points exist within box thresholds.

3.3. Vertical modeling

3.3.1. Height modeling

In height modeling, pseudo points provide a sampling framework for the estimation of ceiling to floor heights. In building interiors, ceilings and floors are mostly planar structures located at the highest and lowest heights, respectively. The maximum and minimum z values for each pseudo point are chosen to construct the ceiling to floor height model. The height modeling process employs RANSAC (Random Sample Consensus), an iterative algorithm that is robust to plentiful outliers in a set of measurements (Fischler & Bolles, 1981). RANSAC consists of two phases: (1) hypothesis and (2) test. In the hypothesis phase, three points are selected from the set of points, and the parameter vectors of the height model, which is a mathematical planar model, are then derived. In the test phase, the fitness of the height model is evaluated in relation to all other data. In the geometric sense, error is defined according to the orthog-

onal distance of points with respect to the mathematical plane. When a sufficient number of points are included within a threshold distance, they are considered as hypothetical inliers. The hypothesis and test phases are conducted iteratively until the maximum number of iterations is reached or until 95% of the points are classified as consensus sets.

Fig. 4 illustrates the concept of modeling ceiling height based on pseudo points. In Fig. 4(a), height models are repeatedly examined to determine whether sufficient points are included in the threshold distance from a given mathematical plane; in Fig. 4(b), the model is accepted only once sufficient points can be classified as inliers; in Fig. 4(c), three height models are constructed from three consensus sets. However, point clouds obtained by laser scanning of interiors are likely to include a variety of clutter. Although maximum points are selected from pseudo points, they are usually contaminated with noise data. The height modeling process assumes that a ceiling (or floor) is described with most points having maximum (or minimum) z values; thus, in Fig. 4(d), the largest consensus is selected in order to construct the ceiling (or floor) height model. However, the initial estimates of the model parameters are derived with the minimum number of points. The least squares

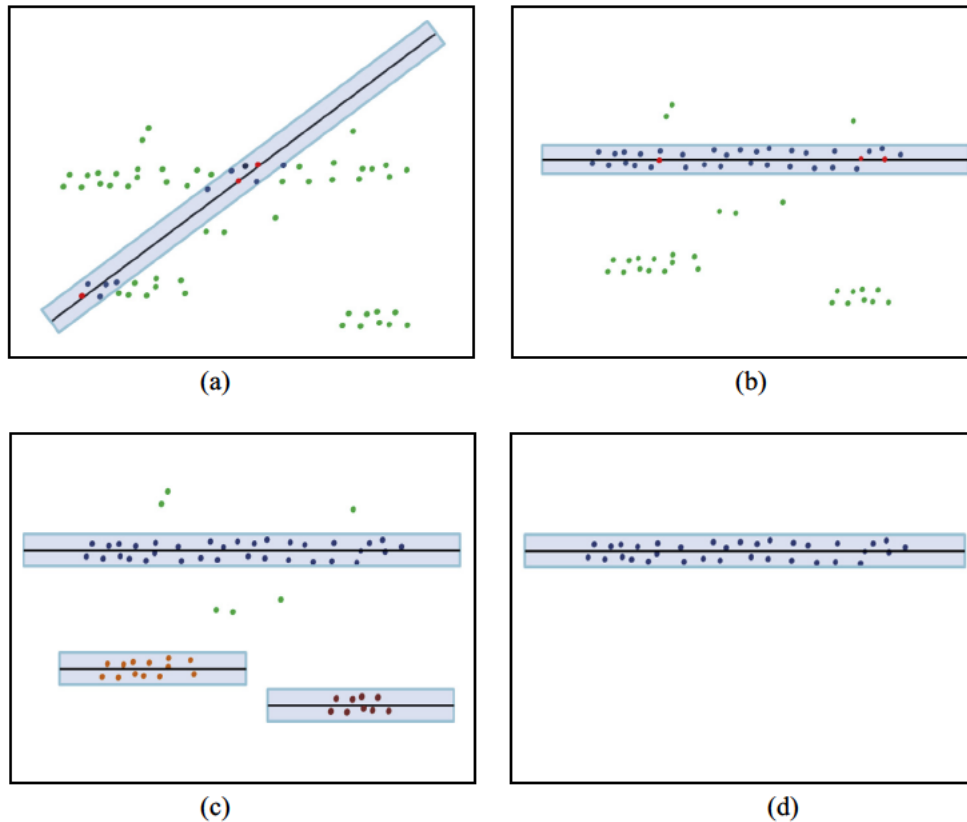


Fig. 4. Ceiling height modeling process with RANSAC: (a) height model creation with three sample points, (b) height model examination in relation to all other data, (c) three height models from three consensus sets, (d) height model determination with the largest consensus set.

method is therefore applied to derive optimized parameter vectors of the ceiling and floor height models.

3.3.2. Filtering

In comparison to building exteriors, building interiors are unique in that most clutter is in empty space bounded by principal building components, such as floors, walls, and ceilings. Clutter is separated from point clouds in the filtering process by reference to height variations. Fig. 5(a) is a profile view of a typical room. The maximum and minimum z values at the same horizontal positions represent the floor and ceiling, respectively. Although walls between the floor and ceiling have z values as high as the maximum, most clutter at given horizontal positions has z values less than the maximum in Fig. 5(b); an offset space from the ceiling is used as the criterion determining whether a pseudo point belongs to clutter or not. The filtering process removes the pseudo point when the offset space is empty. Otherwise, the pseudo point is considered to describe a main structure, such as a wall, and its original points are used for the next step of 2D floor boundary modeling.

3.4. 2D floor boundary modeling

3.4.1. Boundary extraction

The purpose of 2D floor boundary modeling is to define the outline of an interior. Initially, entire point clouds are projected onto a 2D grid plane at a defined spatial resolution. A boundary tracing operation is then applied to extract a 2D floor boundary that consists of numerous line segments in sequential order. However, the tracing grid tends to generate the appearance of a jagged boundary. Necessarily then, a refinement process is followed that involves two main steps: (1) segmentation and (2) regularization. The segmentation process groups line segments according to identical line components of the 2D floor boundary. The regularization process

adjusts line segments belonging to each segmentation group by means of the constraint least squares method. A boundary thus refined has simplified lines that exhibit correct geometric properties, such as orthogonality or parallelism.

3.4.2. Boundary segmentation

In the segmentation process, the Douglas Peucker algorithm (Douglas & Peucker, 1973) is modified to seek the 2D floor boundary's corner points according to which line segments between the corners are grouped into identical line components. In Fig. 6's conceptual illustration of the process, a cylinder of half width (ϵ) classifies points inside of it. The initial extraction of a 2D floor boundary, shown in Fig. 6(a), is an ordered set of points (or line segments). A cylinder is created along the line segments, with the first and last points being the end points. When no points exist within the cylinder, the segmentation method automatically marks the first point to be kept and finds a temporary end point from among the farthest points. When multiple farthest points are chosen, a point in the early sequence becomes a temporary end point for creation of a cylinder (Fig. 6(b)). The cylinder is repeatedly created until the point next to the first point is classified (Fig. 6(c)). As shown in Fig. 6(d), the cylinder proceeds to the next segmentation process, marking the previous temporary end point (in Fig. 6(c)) as the new first point and finding a new temporary end point. The same procedure repeats until the last point becomes the first point, (Fig. 6(g)). The segmentation results in Fig. 6(h) show that all of the line segments are classified into four groups.

If the effect of noisy points is severe, it can incur incorrect segmentation. Hence, a further refinement process is required after segmentation. Assuming the right angle constraint, two line segments are extracted in sequential order; the latter one is tested as to whether it is shorter than ϵ , and the former is connected to the latter within the direction of $\pm 45^\circ$. If the line segments sat

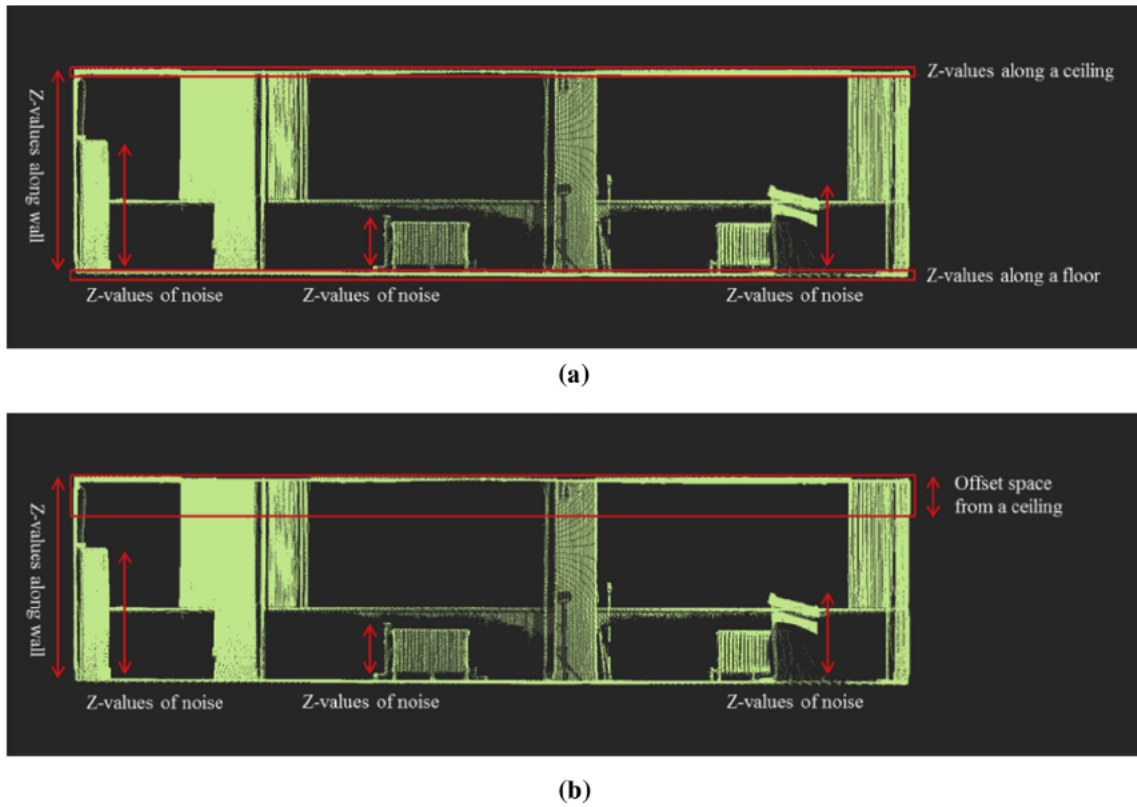


Fig. 5. Height modeling and filtering processes: (a) height variations in the seminar room, (b) offset space for the filtering process.

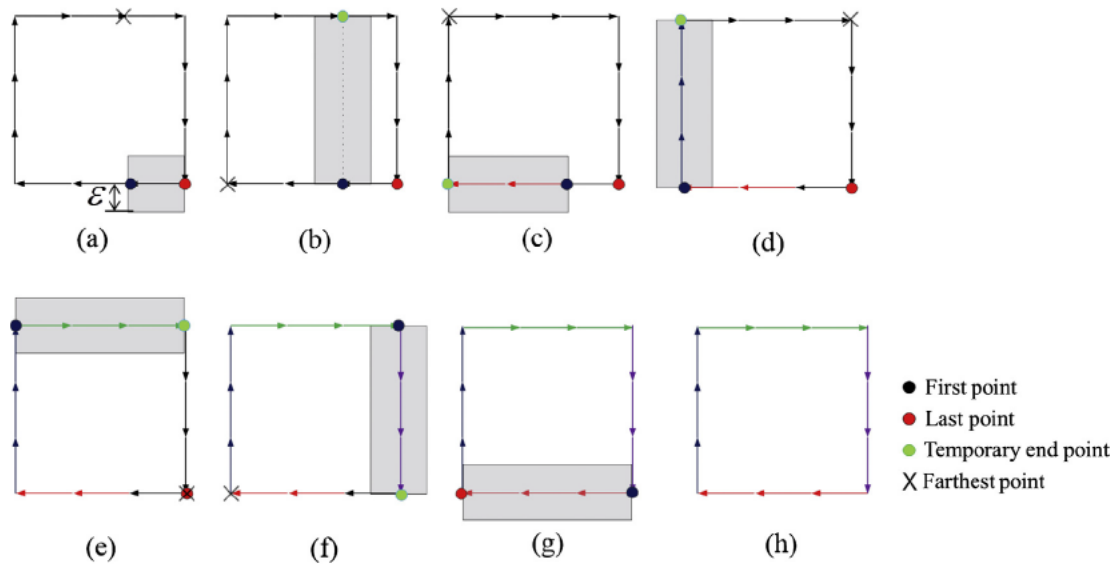


Fig. 6. Segmentation process.

isfy either one of the two conditions, the two line segments are integrated into a single line segment. The refinement iterates until the entire lines are tested; in the final step, the last line segment is checked with the first line segment.

3.4.3. Boundary regularization

In the boundary regularization, a line equation with unknown parameters is formulated according to the points of line segments in each segmentation group as

$$l_i = f_i(\theta_{1i}, \theta_{2i}) = \theta_{1i}x_{ij} + \theta_{2i}y_{ij} + 1 = 0, \quad i = 1, 2, \dots, n; \quad j = 1, 2, \dots, m \quad (2)$$

where l_i : the i th line segments, x_{ij}, y_{ij} : x and y coordinated of the j th points on the i th line segment and θ_{1i}, θ_{2i} : parameter vectors of the i th line segment.

As it is assumed that 2D floor boundaries of typical rooms are mutually perpendicular to each other, a right angle constraint between two line segments is imposed as follows:

$$c_i(\theta_1, \theta_2, \theta_{1+i}, \theta_{2+i}) = \theta'_1 \theta'_{1+i} + \theta'_2 \theta'_{2+i} = 0, \quad i = 1, 2, \dots, n-1 \quad (3)$$

Thus, a system of line equations conforming to the right angle constraint is formulated as

$$(\theta'_1, \theta'_2) = \underset{0}{\operatorname{argmin}} \|f(\theta_1, \theta_2, w_i)\|^2, \quad \text{subject to } c_i(\theta_1, \theta_2, \theta_{1+i}, \theta_{2+i}) = 0 \quad (4)$$

where θ'_1, θ'_2 : optimized parameter vectors of the i th line segment, conforming to the right angle equation and w_i : weight of the i th line segment.

Additionally, in the regularization process, the weight is the number of points in each segmentation group, in relation to which longer lines are more likely to have a dominant influence on the directions of other lines.

3.5. 3D as built modeling

3D as built modeling involves outcomes from the preprocessing, vertical modeling, and 2D floor boundary modeling. A floor (or ceiling) height model obtained from vertical modeling is used to compute floor (or ceiling) heights at horizontal positions of the 2D floor boundary's corners. A 3D wireframe model can then be constructed by extruding a 2D floor boundary with floor ceiling height differences at the corners. The 3D wireframe model, however, defines only the outer shapes of interiors. In BIM, the model needs to describe two essential components: (1) the 3D as built representation of the building based on objects and (2) the properties of the building beyond the graphical representation (CRC, 2009). Generally, in 3D model construction, clutter is an inessential component; however, in the proposed approach, clutter data is considered as an important source of information including not

only geometric details of building objects but also the objects' implied semantic attributes and relationships. Thus, the BIM tool (AutoCAD Revit 2013) is employed to build the 3D as built model, for which the 3D wireframe model and clutter data are imported into the BIM tool.

The BIM tool allows modelers to expedite a 3D as built model using 3D building objects, referred to as "Families," from the building models database. In the BIM modeling environment, the manual modeling process mainly entails three steps: (1) grid creation, (2) main object modeling, and (3) detailed object modeling. Grid creation defines the 3D indoor space to be modeled, main object modeling creates a floor, a ceiling, and walls in accordance with the 3D wireframe models, and, in detailed object modeling, the remaining points are utilized to create windows and doors (Kristine Fallon Associates, 2012; Woo, Wilsmann, & Kang, 2010a).

4. Test sites and application

4.1. Overview

In scanning test sites, FARO Focus 3D, a phase based laser scanner, was employed to collect detailed and accurate as built point data. Despite the shorter range of the time of flight scanner, the laser scanner is appropriate for indoor spaces in that it can rapidly collect dense point cloud data. In the present study, for the purposes of evaluation and validation, the proposed method was applied to two typical rooms selected as test sites: a seminar room and an office (Fig. 7). The scanning results for these sites are illustrated in Table 1. The seminar room is larger than the office but has little clutter in the open space. Thus, for data acquisition purposes, the laser scanner was set up at two locations. In the case of the office, a variety of clutter occupies the relatively small space. Despite the laser scanner having been set up at five locations, the

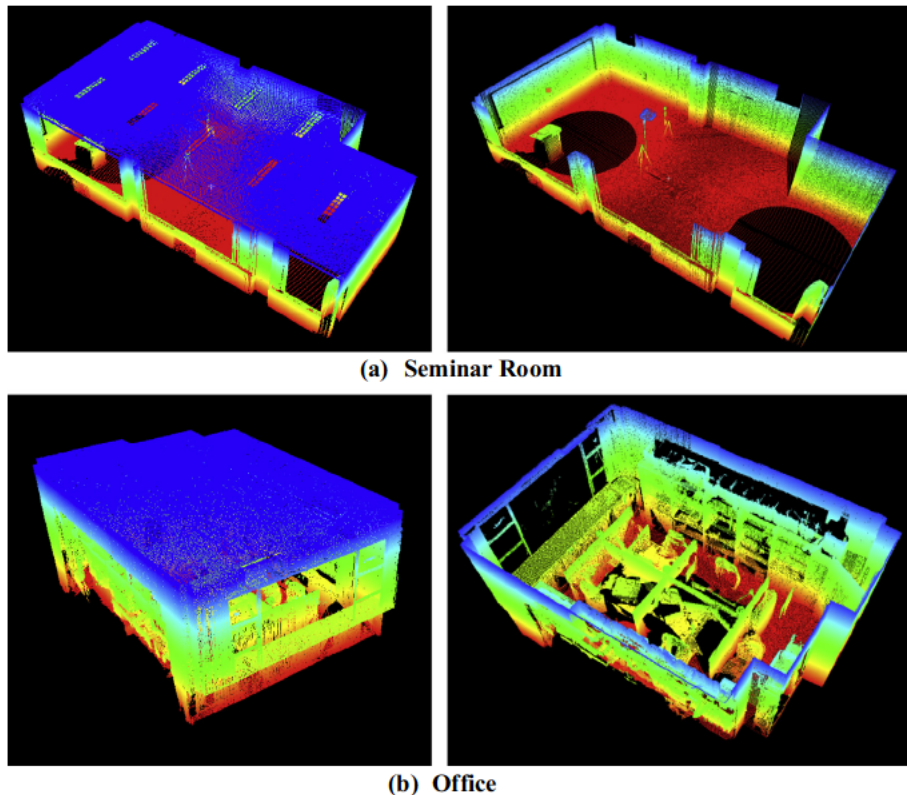


Fig. 7. Test sites: perspective view (left) and inside view with ceiling points removal (right).

Table 1
Test sites and surveying results.

	Seminar room	Office
Number of scanning sites	2	5
Dataset size (.xyz)/point number	120 MB/4,229,468	300 MB/10,759,419

point clouds unavoidably included occlusions by desks, chairs, and bookshelves. Consequently, point clouds of greater size than those of the seminar room were obtained. The remainder of this paper analyzes the modeling outcomes generated in each step of the proposed method and represented in Figs. 8–11. Table 2 defines the corresponding parameters. As the final product of the proposed method is a 3D wireframe model combined with clutter, Autodesk Revit 2013 was employed to create a 3D as built model in BIM. The modeling results are shown in Fig. 12.

4.2. Parameter selection

The proposed method requires parameters for preprocessing, vertical modeling, and 2D floor boundary modeling. The preprocessing parameter is the box threshold at which pseudo points are created. The two parameters in the vertical modeling are (1) the RANSAC threshold applied to the construction of the ceiling and floor height models and (2) the offset space used to identify clutter from point clouds. As a pseudo point is created with all original points within the box threshold, pseudo points at regular intervals provide a sample points framework within which the height models can be constructed with RANSAC. Additionally, pseudo points are used to characterize a point distribution along a vertical direction, to which an offset space and height models are applied for filtering clutter in point clouds.

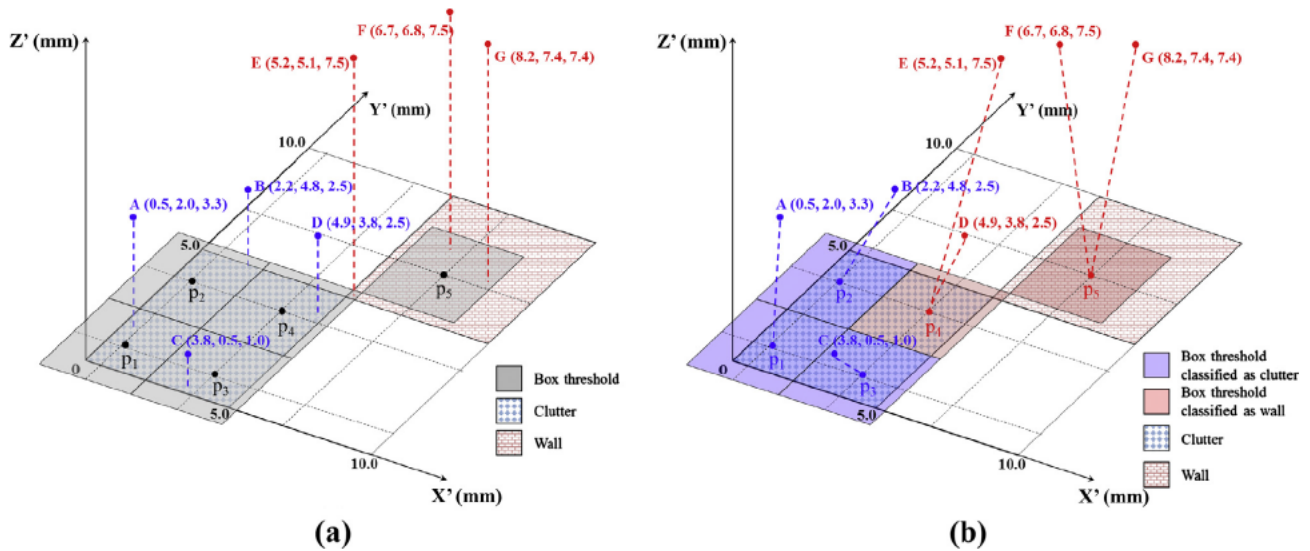


Fig. 8. Conceptual view of incorrect pseudo point creation: (a) created pseudo points on clutter (p_1, p_2, p_3, p_4) and walls (p_5); (b) filtered pseudo points associated with the original points.

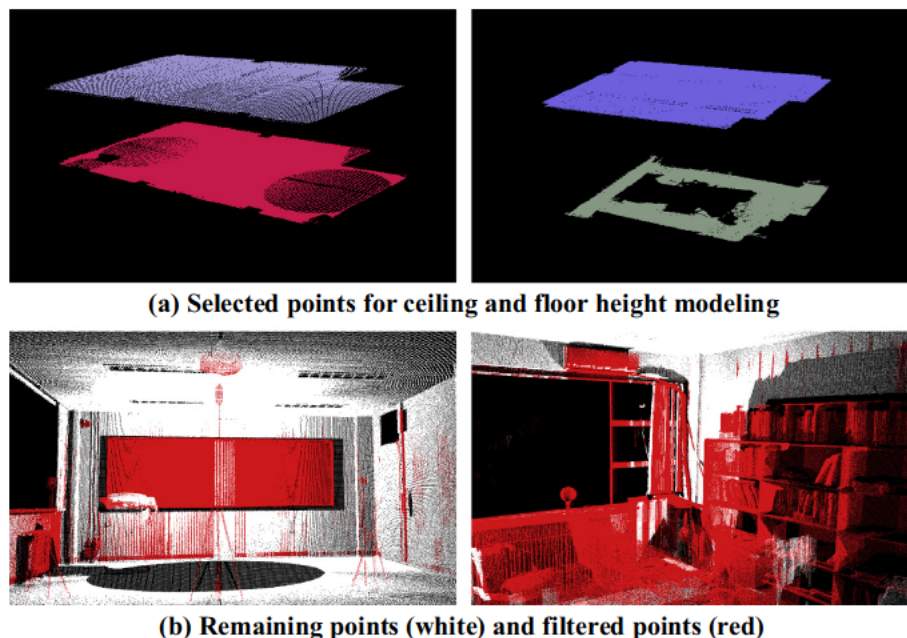


Fig. 9. Preprocessing results: the seminar room (left) and the office (right). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

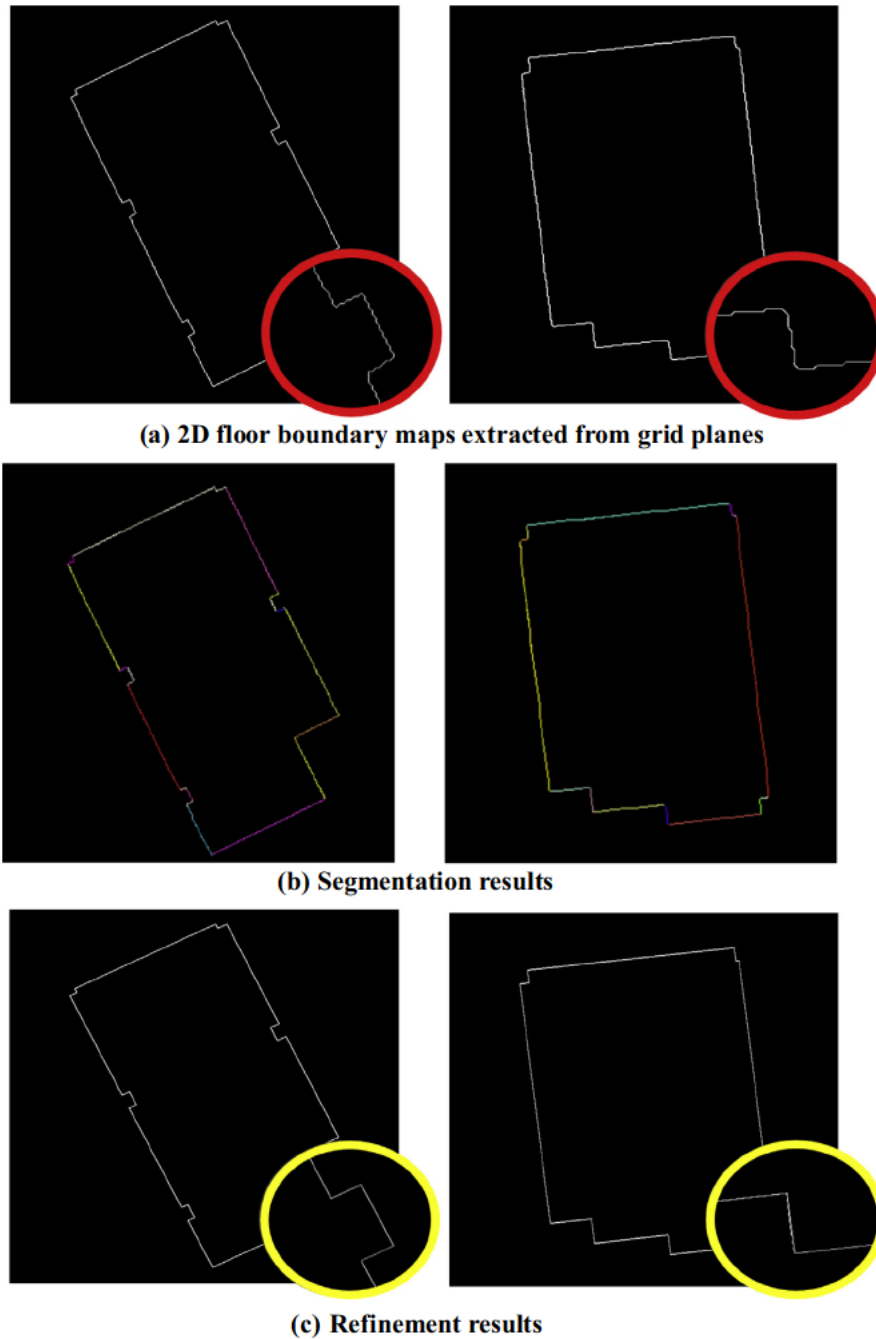


Fig. 10. 2D floor map boundary modeling results: (left) the seminar room and (right) the office.

In the preprocessing and vertical modeling stages, a smaller box threshold indicates a greater number of pseudo points. A greater amount of time is required to visit each pseudo point and retrieve its associated points. However, accurate ceiling and floor height models can be constructed with a great number of points with maximum and minimum z values. Additionally, a rigorous filtering process is conducted to detect smaller clutter, specifically by examining height variations in pseudo points within a smaller box threshold. When a wider box threshold is determined, the preprocessing takes less time; however, with a wider box threshold, a smaller number of pseudo points can incur inaccurate filtering results, as shown in Fig. 8. In Fig. 8(a), the original points, A, B, C, D and E, F, G, represent the clutter and the wall, respectively. Although the centers of pseudo points $p_1 \sim p_4$ are inside the clutter

area, some parts of those pseudo points' areas exceed the clutter's boundary, because the box threshold is greater than half the size of the clutter. This is particularly so in the case of p_4 ; it partially contains the wall, and thus the original point E on the wall is classified as p_4 , as shown in Fig. 8(a). In the filtering phase, since the clutter is separated from point clouds by reference to maximum height, the pseudo point p_4 will be classified as wall. Therefore, the original point D within the box threshold of p_4 will be incorrectly classified as wall. This might also happen for the other pseudo points $p_1 \sim p_3$. If so, the entire clutter would not be detectable, which incurs incorrect floor boundary extraction in the next step. Accordingly, a box threshold less than half the size of the smallest clutter is desirable, because it allows at least one pseudo point to be fully inside the clutter area.

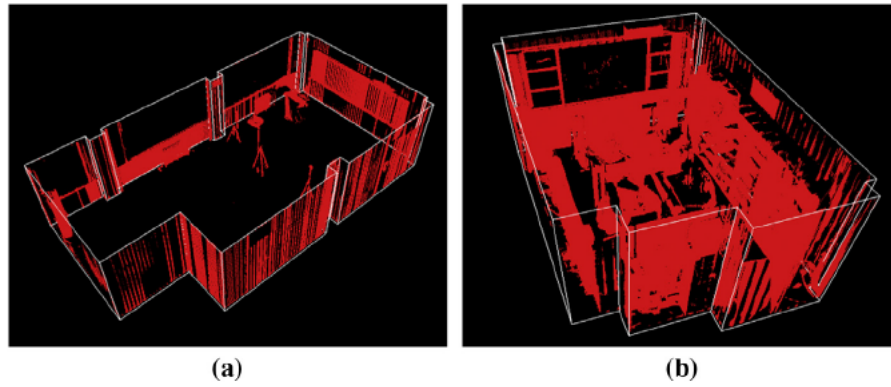


Fig. 11. 3D wireframe model with clutter: (a) the seminar room and (b) the office.

Table 2
Parameter selections in the proposed approach.

Parameters		Seminar room (cm)	Office (cm)
Preprocessing	Spacing interval (Pseudo point)	5.0	5.0
	RANSAC	1.0	1.0
Vertical modeling	Min./Max. offset (Filtering)	1.5–2.0	1.5–2.0
	Tracing grid size (Boundary tracing)	2.5	2.0
2D floor boundary modeling	Cylinder width (Segmentation)	5.0	3.0

The two parameters that need to be controlled in 2D floor boundary modeling are (1) a tracing grid size to delineate the floor boundary outlines and (2) a cylinder width by which to segment the outlines according to identical line components. The tracing grid size and cylinder width are closely related to the complexity of a floor boundary. A smaller cell size in the tracing grid can delineate a detailed outline with a greater number of line segments. In contrast, when a larger cell size is chosen, a simplified outline is extracted with a smaller number of line segments. However, an initial floor boundary extraction is likely to have a zigzag pattern made up of corners at various angles. Cylinder based segmentation is used to group line segments according to identical line components. As is the case with the tracing grid size, a cylinder with a wider width is appropriate for a simple floor boundary. However, if the cylinder width is much greater than the minimum size of the line components, the floor boundary will be oversimplified in the regularization process. Thus, in floor boundary modeling, what is considered to adequately delineate a floor boundary is a tracing grid size equal to or less than the quarter length of the minimum line. Considering the irregular pattern in line segments is affected by the tracing grid, segmentation uses a cylinder width slightly greater than the tracing grid size.

4.3. Modeling results and evaluation

4.3.1. Preprocessing and vertical modeling

In preprocessing and vertical modeling, a pseudo point is the basis for height modeling and filtering clutter from point clouds. At both test sites, the box threshold creation for pseudo points was set to 5 cm, and the RANSAC threshold was set to 1 cm, according to which ceiling and floor height models were constructed with points of minimum and maximum height. In the filtering process, pseudo points every 5 cm, totaling 10,041 points for the seminar room and 24,433 points for the office, are sufficient to discern small and tiny clutter in the horizontal dimension as well as to characterize a point distribution along the vertical direction. The offset space was determined according to the maximum clutter

heights at both test sites, where the seminar room has a ceiling mounted projector and the office a wall mounted air conditioner. Thus, for rigorous filtering of clutter, the minimum and maximum offsets to the ceiling were set up as 1.5 cm and 2 cm, respectively. Fig. 9(a) shows the consensus sets for the test site height modeling. As only a small amount of clutter existed in the seminar room, the laser scanner was set up at two locations. However, due to the limited FOV (Field of View) in the vertical direction, sparse points in a circular pattern were shown in the floor consensus set. In the case of the office, the floor consensus set had occlusions by bookshelves along the walls and desks and chairs in the middle. The filtering results for the test sites are shown in Fig. 9(b), where the red highlighted³ clutter is a blackboard and steam heaters in the seminar room and bookshelves and window frames in the office.

4.3.2. 2D floor boundary modeling

In 2D floor boundary modeling, point clouds are projected onto a 2D grid plane. A boundary tracing grid is then applied to extract the 2D floor boundaries. In comparison with the office, the seminar room has a more complex floor boundary with a greater number of line components. The traced boundary could not be directly used, due to the irregular shapes and artifacts shown in Fig. 10(a). Further refinement was conducted with segmentation and regularization. Cylinder widths greater than the tracing grid sizes were selected, as indicated in Table 2, for segmentation of the floor boundaries in the seminar room (5 cm) and office (3 cm). For visual interpretation, the segmented groups are highlighted with different colors in Fig. 10(b). In the regularization, constraint least squares method was applied to adjust the line components from the segmented line segments. The refinement results in Fig. 10(c) signal that regularity was achieved by straightening zigzag lines and enforcing the right angle property to adjunct lines. As a result, the slopes of the lines in the floor boundaries are either parallel or perpendicular.

³ For interpretation of color in Fig. 9, the reader is referred to the web version of this article.

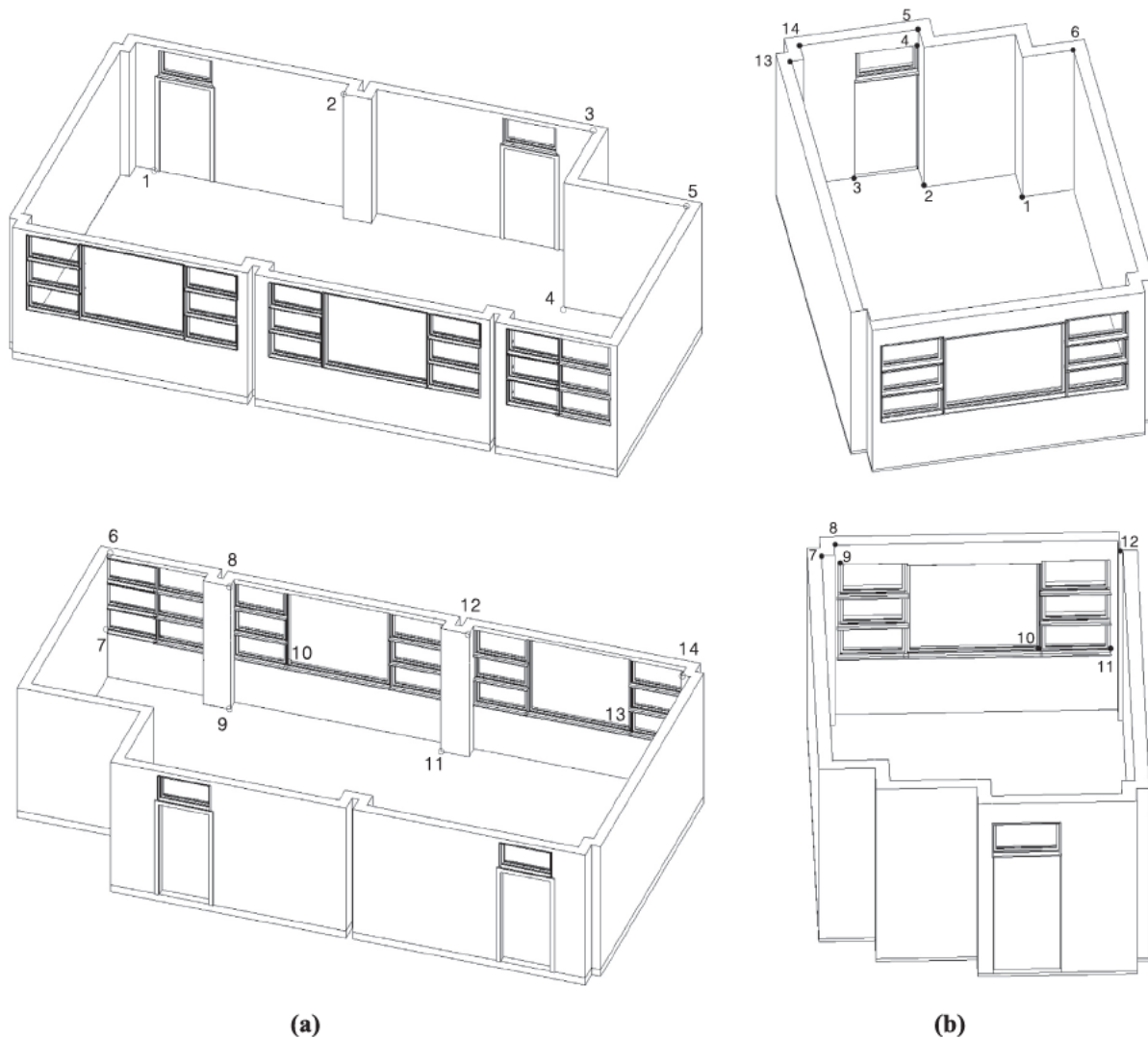


Fig. 12. 3D as-built modeling results: (a) the seminar room and (b) the office.

4.3.3. 3D as built modeling

Geometric modeling productivity improvements by means of simplified lines can be found in Heo et al. (2013) and Jung et al. (2014). In those cases, such lines, as extracted, are substituted for the point clouds of the structural components and thus reduce the huge data size of the original point clouds. Additionally, the simplified lines and clutter enable the modeler to easily identify the structural components and their relations to the other components, which facilitates and enhances productivity in as built BIM creation. In the present study, the final products, regularized 3D wireframes with clutter (Fig. 11), were imported into Autodesk Revit 2013. Note that the present study assumed the materials for the walls, ceiling, and other structures, because the main focus was geometric modeling. As built BIM production in Revit consists of four main phases: (1) grid creation; (2) walls and floor creation; (3) roof (or ceiling) creation, and (4) detail modeling (Jung et al., 2014; Kristine Fallon Associates, 2012). Regularized 3D wireframes, which describe the locations and arrangements of walls, ceiling, and floor, are particularly useful in phases 2 and 3. Moreover, in phase 4, the clutter provides information for the modeling of details (doors and windows). In the present study, using the wireframes and clutter as guidance, the efficiency of the as built BIM creation process was improved by 15.4% for the seminar room and 15.0% for the office. However, it is difficult to demonstrate productivity improvement with the current results, because the

combined total time consumption of as built BIM creation for the two test sites was only approximately 20 min. In light of Heo et al. (2013), who achieved a significant efficiency improvement (23.5–47.4%) in the modeling time for 10 buildings using wire frames and clutter as guidance, the proposed approach might be expected to achieve similar efficiency gains for larger indoor environments.

4.3.4. Accuracy assessment

The final products of the 3D as built models, shown in Fig. 12, are compared with a set of total station point measurements used as reference points. In the mapping accuracy assessment, comparisons are based on clearly identifiable features, such as corners of walls, doors, and window frames. Reference points should be well distributed over the indoor space, as positional differences reflect the overall accuracy of 3D as built models. In practice, 14 reference points are measured for each test site. However, the reference points in the seminar room, due to its open space, are more scattered than in the office, which is filled with dense clutter (i.e., bookshelves along the walls). The accuracy of the 3D as built model was quantified according to the Euclidean average distance error, ε_d , as

$$\varepsilon_d = \frac{1}{n} \sum_{i=1}^n \|Ra_i - b_i\| \quad (5)$$

Table 3

Accuracy assessment results for the seminar room (unit: meters).

Target ID	Error vector X	Error vector Y	Error vector Z	Error
1	−0.053	0.039	0.009	0.066
2	−0.027	0.005	0.012	0.03
3	0.010	−0.008	0.01	0.016
4	−0.041	−0.012	−0.01	0.043
5	−0.017	−0.001	0.015	0.022
6	0.050	0.018	0.021	0.058
7	0.047	0.000	−0.086	0.098
8	−0.014	0.023	0.016	0.031
9	0.025	0.014	−0.008	0.03
10	0.005	−0.041	−0.008	0.042
11	−0.023	0.040	0.006	0.046
12	−0.014	0.021	0.011	0.027
13	−0.025	−0.014	0.011	0.031
14	0.076	−0.084	0	0.113
Average error				0.047
RMSE	0.036	0.031	0.026	0.054

Table 4

Accuracy assessment results for the office (unit: meters).

Target ID	Error vector X	Error vector Y	Error vector Z	Error
1	−0.023	0.002	0	0.023
2	−0.038	0.021	−0.028	0.052
3	−0.027	0.004	−0.006	0.028
4	−0.024	0.010	−0.052	0.058
5	−0.016	0.004	0.005	0.017
6	−0.023	0.007	0.005	0.025
7	0.004	−0.017	0.007	0.019
8	0.039	−0.020	0.01	0.045
9	0.038	0.058	−0.023	0.073
10	0.019	−0.043	0.016	0.05
11	0.037	−0.110	0.035	0.121
12	0.022	0.023	0.009	0.033
13	−0.014	0.040	0.009	0.043
14	0.006	0.022	0.012	0.025
Average error				0.044
RMSE	0.026	0.039	0.021	0.051

where a_i : error vector from origin to i th check point in a model space, b_i : error vector from origin to i th reference point in a measurement space, R : rotation matrix and t : translation vector.

In Eq. (5), the 3D conformal transformation with a unit scale factor is used to bring the model coordinates in line with the reference points. The points corresponding to the reference points in the 3D as built models (Fig. 12) are shown with their error vectors in Tables 3 and 4. The average error indicates that the overall accuracies for the seminar room and office were 0.047 m and 0.044 m, respectively. The quality of the 3D as built models can also be evaluated by the Root Mean Square Error (RMSE) and Spherical Accuracy Standard (SAS). The RMSE is computed by

$$RMSE_x = \sqrt{\sum_{i=1}^n (x_{a,i} - x_{b,i})^2} \quad (6)$$

where $x_{a,i}$ and $x_{b,i}$ are the x coordinates of the destinations of vectors a_i and b_i , respectively. The RMSE in each direction (x , y , and z) of each room is listed in Tables 3 and 4, ranging between 0.021 m and 0.039 m. The SAS is defined as the spherical radius for a 90% probability sphere (Greenwalt and Schultz, 1968) and is computed by

$$SAS = 2.5 \times 0.3333 \times (RMSE_x + RMSE_y + RMSE_z) \quad (7)$$

For the two rooms, the SAS values were 0.078 m and 0.071 m, respectively. It can be said that the proposed approach generated 3D as built models within a positional accuracy of 0.078 m at the 90% confidence level. The results of the accuracy assessment indicate that errors in indoor models would be expected to be associ-

ated with tracing grid sizes, in that identical parameters were set up for the preprocessing and vertical modeling. As shown in Table 2, the tracing grid sizes in the seminar room and office were set up as 2.5 cm and 2 cm, respectively. As the floor boundaries are the basis for creating a 3D wire frame model with estimated heights, the accuracy for the seminar room was better than that for the office. The relationship between parameter settings and mapping accuracy in the next stage of the algorithm is definitely worth studying further.

5. Summary and conclusions

A 3D as built BIM model facilitates the utilization and sharing of building information in the construction process. Thus, fast and accurate reconstruction of a 3D as built model is essential to collaborative construction management. For these purposes, the 3D laser scanners are widely used, owing specifically to its capability to quickly collect massive point clouds depicting the “as built” conditions of building interiors. However, manual indoor reconstruction still suffers from low productivity and inaccurate mapping results. Therefore, to improve the 3D indoor mapping process, a semi automated method entailing four major processes—preprocessing, vertical modeling, 2D floor boundary modeling, and 3D as built modeling—is proposed in this paper. The major innovations of this study are as follows: first, the 3D wireframe models defined an outline of the building interior, with removal of the point clouds on principal building components, such as the ceiling, floor, and walls. Consequently, the huge size of point clouds for as built BIM was drastically reduced. Second, a pseudo point structure for storing the coordinates of nearby original point data was proposed to facilitate height modeling and point cloud filtering. Additionally, the 3D wireframe enabled modelers to efficiently identify clutter inside of the principal building components and improve productivity of the 3D model production. Third, the refinement process, including segmentation and regularization, allows for provision of an accurate floor boundary. Moreover, clutter data remaining in point clouds was used to model detailed building objects, such as windows and doors. The proposed method was evaluated on the basis of point clouds acquired from two typical rooms in a building, in which the modeling results from each processing step confirmed the effectiveness of the proposed approach. Furthermore, the mapping accuracy assessment indicated that the constructed 3D as built models were approximately 2–4 cm in RMSE on each axis, which satisfied the error tolerance of “level 1” (5 cm), according to the guidelines of the General Services Administration for BIM accuracy (General Services Administration, 2009).

The proposed approach will enable the more efficient and accurate as built BIM creation that is required for various applications. During the construction phase, it provides powerful media for progress monitoring, which can be used for quick and remote analysis of construction performance. Additionally, integration of as planned and as built models enables the identification and isolation of elements deviating from the accepted tolerances. Finally, the as built conditions provide the owner with a digital 3D model of a building and its various systems that can greatly facilitate operation and maintenance procedures (Azhar, 2011; Golparvar Fard, Peña Mora, & Savarese, 2011). Additionally, it is expected that there are further potential applications of the proposed approach, for example, improved renovation planning, building component location, maintainability determination, provision of real time data access, facilitation of space management, and historical building preservation and renovation (Klein, Li, & Becerik Gerber, 2012; Tang et al., 2010; Woo, Wilsman, & Kang, 2010b).

Although the proposed approach was proven to be an efficient means of indoor as built BIM creation, automated modeling of geo-

metric details (doors and windows), which is expected to reduce data size and, thereby, enhance productivity, would definitely be worth investigating. Additionally, for improved accuracy, evaluation of the proposed approach in different types of environments should also be considered. Still, the proposed geometric modeling is limited to indoor surface structures (boundary representation), whereas most BIMs are based on semantically rich solid modeling (Xiong et al., 2013). Further research should be undertaken in order to facilitate the SCAN to BIM process by converting the given wire frame model into a solid model incorporated with semantic information. Additionally, for the proposed method's heuristic determination of modeling parameters, the regularization method is limited to right angled boundaries. To enable refinement of 2D floor boundaries consisting of line components meeting at various angles, a new regularization method is required. Moreover, for enhanced productivity and accuracy with 3D as built modeling, the modeling of geometric details and semantic information in and between building objects should be considered.

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References

- Arayici, Y. (2007). An approach for real world data modelling with the 3D terrestrial laser scanner for built environment. *Automation in Construction*, 16, 816–829.
- Arayici, Y. (2008). Towards building information modelling for existing structures. *Structural Survey*, 26, 210–222.
- Azhar, S. (2011). Building information modeling (BIM): Trends, benefits, risks, and challenges for the AEC industry. *Leadership and Management in Engineering*, 11, 241–252.
- Budroni, A., & Böhm, J. (2010). Automatic 3d modelling of indoor Manhattan-world scenes from laser data. *ISPRS commission V mid-term symposium: Close range image measurement techniques* (pp. 115–120).
- CRC (2009). *National guidelines for digital modelling*. Cooperative Research Centre for Construction Innovation, Brisbane, Australia.
- Douglas, D. H., & Peucker, T. K. (1973). Algorithms for the reduction of the number of points required to represent a digitized line or its caricature. *Cartographica: The International Journal for Geographic Information and Geovisualization*, 10, 112–122.
- Fischler, M. A., & Bolles, R. C. (1981). Random sample consensus: A paradigm for model fitting with applications to image analysis and automated cartography. *Communications of the ACM*, 24, 381–395.
- Furukawa, Y., Curless, B., Seitz, S. M., & Szeliski, R. (2009). Reconstructing building interiors from images. *IEEE 12th international conference on computer vision* (pp. 80–87). IEEE.
- General Services Administration (2009). *BIM guide for 3D imaging, ver. 1.0*. (p. 53). U.S. General Services Administration.
- Golparvar-Fard, M., Peña-Mora, F., & Savarese, S. (2011). Integrated sequential as-built and as-planned representation with D 4 AR tools in support of decision-making tasks in the AEC/FM industry. *Journal of Construction Engineering and Management*, 137, 1099–1116.
- Greenwalt, C., & Schultz, M. (1968). *Principles of Error Theory and Cartographic Applications*: ACIC Technical Report No. 96, Aeronautical Chart and Information Center, U.S. Air Force, St. Louis, Missouri.
- Han, S., Cho, H., Kim, S., Jung, J., & Heo, J. (2012). Automated and efficient method for extraction of tunnel cross sections using terrestrial laser scanned data. *Journal of Computing in Civil Engineering*, 27, 274–281.
- Han, S. H., Heo, J., Sohn, H. G., & Yu, K. (2009). Parallel processing method for airborne laser scanning data using a pc cluster and a virtual grid. *Sensors*, 9, 2555–2573.
- Henry, P., Krainin, M., Herbst, E., Ren, X., & Fox, D. (2012). RGB-D mapping: Using Kinect-style depth cameras for dense 3D modeling of indoor environments. *The International Journal of Robotics Research*, 31, 647–663.
- Heo, J., Jeong, S., Park, H.-K., Jung, J., Han, S., Hong, S., et al. (2013). Productive high-complexity 3D city modeling with point clouds collected from terrestrial LiDAR. *Computers, Environment and Urban Systems*, 41, 26–38.
- Isikdag, U., Zlatanova, S., & Underwood, J. (2013). A BIM-oriented model for supporting indoor navigation requirements. *Computers, Environment and Urban Systems*, 41, 112–123.
- Jung, J., Hong, S., Jeong, S., Kim, S., Cho, H., Hong, S., et al. (2014). Productive modeling for development of as-built BIM of existing indoor structures. *Automation in Construction*, 42, 68–77.
- Kersten, T., Sternberg, H., & Stierner, E. (2005). First experiences with terrestrial laser scanning for indoor cultural heritage applications using two different scanning systems. *Proceedings of the ISPRS working group* (Vol. 5, pp. 24–25).
- Klein, L., Li, N., & Becerik-Gerber, B. (2012). Imaged-based verification of as-built documentation of operational buildings. *Automation in Construction*, 21, 161–171.
- Kristine Fallon Associates, I. (2012). *Revit architecture 2012: Quick start – Using Revit to increase productivity*. Kristine Fallon Associates Inc.
- Li, X., Claramunt, C., & Ray, C. (2010). A grid graph-based model for the analysis of 2D indoor spaces. *Computers, Environment and Urban Systems*, 34, 532–540.
- Mao, B., Harrie, L., & Ban, Y. (2012). Detection and typification of linear structures for dynamic visualization of 3D city models. *Computers, Environment and Urban Systems*, 36, 233–244.
- Over, M., Schilling, A., Neubauer, S., & Zipf, A. (2010). Generating web-based 3D City Models from OpenStreetMap: The current situation in Germany. *Computers, Environment and Urban Systems*, 34, 496–507.
- Richter, R., & Döllner, J. (2014). Concepts and techniques for integration, analysis and visualization of massive 3D point clouds. *Computers, Environment and Urban Systems*, 45, 114–124.
- Sansoni, G., Trebeschi, M., & Docchio, F. (2009). State-of-the-art and applications of 3D imaging sensors in industry, cultural heritage, medicine, and criminal investigation. *Sensors*, 9, 568–601.
- Tang, P., & Akinci, B. (2012). Automatic execution of workflows on laser-scanned data for extracting bridge surveying goals. *Advanced Engineering Informatics*, 26, 889–903.
- Tang, P., Huber, D., Akinci, B., Lipman, R., & Lytle, A. (2010). Automatic reconstruction of as-built building information models from laser-scanned point clouds: A review of related techniques. *Automation in Construction*, 19, 829–843.
- Valero, E., Adan, A., & Cerrada, C. (2012). Automatic method for building indoor boundary models from dense point clouds collected by laser scanners. *Sensors*, 12, 16099–16115.
- Volk, R., Stengel, J., & Schultmann, F. (2014). Building Information Modeling (BIM) for existing buildings—Literature review and future needs. *Automation in Construction*, 38, 109–127.
- Woo, J., Wilsmann, J., & Kang, D. (2010a). Use of as-built building information modeling. *Construction research congress* (pp. 538–547).
- Woo, J., Wilsmann, J., & Kang, D. (2010b). Use of as-built building information modeling. *Construction research congress* (pp. 538–547).
- Xie, X., Zhu, Q., Du, Z., Xu, W., & Zhang, Y. (2013). A semantics-constrained profiling approach to complex 3D city models. *Computers, Environment and Urban Systems*, 41, 309–317.
- Xiong, X., Adan, A., Akinci, B., & Huber, D. (2013). Automatic creation of semantically rich 3D building models from laser scanner data. *Automation in Construction*, 31, 325–337.
- Zhao, J., Zhu, Q., Du, Z., Feng, T., & Zhang, Y. (2012). Mathematical morphology-based generalization of complex 3D building models incorporating semantic relationships. *ISPRS Journal of Photogrammetry and Remote Sensing*, 68, 95–111.