Advanced Engineering Informatics xxx (2015) xxx–xxx

Contents lists available at ScienceDirect

Advanced Engineering Informatics

journal homepage: www.elsevier.com/locate/aei

An approach to combine progressively captured point clouds for BIM update

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ARTICLE INFO

Article history:
Received 5 August 2014
Received in revised form 19 April 2015
Accepted 31 August 2015
Available online xxxx

Keywords:
Progressive point clouds
Laser scanning
Building information model (BIM) updating
Complete
As-planned BIM

ABSTRACT

Building information models (BIMs) provide opportunities to serve as an information repository to store and deliver as-built information. Since a building is not always constructed exactly as the design information specifies, there will be discrepancies between a BIM created in the design phase (called as-designed BIM) and the as-built conditions. Point clouds captured by laser scans can be used as a reference to update an as-designed BIM into an as-built BIM (i.e., the BIM that captures the as-built information). Occlusions and construction progress prevent a laser scan performed at a single point in time to capture a complete view of building components. Progressively scanning a building during the construction phase and combining the progressively captured point cloud data together can provide the geometric information missing in the point cloud data captured previously. However, combining all point cloud data will result in large file sizes and might not always guarantee additional building component information. This paper provides the details of an approach developed to help engineers decide on which progressively captured point cloud data to combine in order to get more geometric information and eliminate large file sizes due to redundant point clouds.

1. Introduction

For every construction project, the general contractor of a project is required to hand over the as-built documentation to the owner at the end of that project. The main challenge with the handover process is to ensure that the captured building information is complete and reflects the actual building conditions [1–3]. Building information models (BIMs) provide opportunities to be used as information repositories to store and deliver as-built information due to their flexibility in capturing and exchanging digital information about projects.

While it is possible to convert an as-designed BIM created in the design phase into an as-built BIM, extensive surveying is needed to measure the discrepancies between an as-designed BIM and actual building conditions. Laser scanning technology is able to capture accurate geometric information in a timely manner. Hence, point clouds captured by laser scans can be used as a reference to update an as-designed BIM into an as-built BIM. However, point cloud data collected at a single point in time typically is not capable of providing all the geometric information required for updating an as-designed BIM due to: (a) having periodic occlusions on a construction scene because of temporary work, machinery, laborers, and materials, (b) buried or hidden building components behind the finished surfaces (e.g., ductwork that are hidden behind ceiling tiles) and (c) building components that are not scheduled to be constructed/installed prior to the scanning.

Scanning a building at discrete points in time during its construction process (called as progressive scanning in this paper) and combining these scans together could provide a more complete set of geometric information, which is necessary for updating building components in a BIM. The value of progressively scanning a building during its construction process and combining these point cloud data sets together are investigated in this paper through an experimental analysis that used a renovation project as the testbed.

Combining point clouds together could result in a file with size that is difficult to process and store, given that each point cloud often contains millions of data points and its size could range between a few hundred megabytes to a few gigabytes depending on the scanning range and resolution [4,5]. There is a trade-off between obtaining a more complete set of geometric information by combining all of the progressively captured point clouds and

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http://dx.doi.org/10.1016/j.aei.2015.08.005
1474-0346/

reducing the file size by only combining a subset of point clouds that could provide all the necessary geometric information for the components of interest. To address this challenge, there is a need for an approach that would enable evaluating geometric information contained in a point cloud data set and supporting the decision of selecting a subset of available point clouds without sacrificing the file manipulation and handling due to large file sizes.

This paper first introduces an experimental analysis that evaluate and quantify the value of using progressive point clouds to support the BIM updating process. Second, this paper presents an approach that evaluates the information contained in point clouds captured at different times and selects the least number of point clouds for combination. The goal of this approach is to register less number of point clouds and hence minimize the file size of the registered point cloud days and the corresponding processing time while maximizing the coverage of the geometric information to be used for BIM update. The developed approach targets on surfaces of building components and quantifies the geometric information associated with the target surfaces captured within each point cloud data. The approach then compares the coverage of information (e.g., the percentage of building surfaces captured within a point cloud) provided by each point cloud data and assesses the additional information gained by the combined point cloud data. Based on the analysis, the approach accesses the value of geometric information and prioritizes the scans for minimizing the file size and maximizing the coverage.

2. Related research studies

The research work presented in this paper builds on the previous research studies in relation to (1) evaluation of the quality and quantity of information captured by point clouds, (2) point cloud registration approaches, and (3) scan planning approaches.

2.1. Evaluation of the quality and quantity of information captured by point clouds

Previous studies that have evaluated the quality and quantity of information captured by point cloud data can be grouped into two: (a) Approaches that assess the accuracy of point cloud data by comparing the measurements on real physical objects to the measurements taken in the corresponding point cloud data, and (b) Approaches that compare the point cloud data to other sources of corresponding reference data, such as building information models.

The first group of research studies focuses on assessing the accuracy of geometric information captured by point cloud data. To support the assessment, these research studies have suggested taking measurements on real physical objects and comparing the measurements to the measurements taken from the corresponding objects captured in point cloud data [6–9]. The results of these research studies are used to support different engineering applications, including (a) the identification of the factors (e.g., the resolution and range of laser scanners, the reflectivity of scanned surfaces) that could impact the accuracy of captured point cloud data [6–8,10–13], and (b) the evaluation of the accuracy of point cloud data captured by laser scanners and assessing the applicability of using point cloud data to support a specific task (e.g., 3D surveying, quality control, surface flatness detection, etc.) [14–16].

Studies that evaluate the accuracy of captured point cloud data for specific engineering applications well align with the work presented in this research in terms of assessing the quality of geometric information captured by laser scanners. However, one main difference between the previous approaches described above and the research presented in this paper is that such studies do not focus on evaluating the completeness of data provided by a point cloud (i.e., whether or not the entire surfaces of a building component can be seen in a point cloud). The research presented in this paper differs from these previous studies with respect to quantifying the geometric information captured by a point cloud.

The second group of research studies formulated a deviation-based approach in order to identify the differences between point cloud data and a reference model, such as a building information model [17–22]. The reference models assumed to reflect the ground truth for different geometric information, such as the location, dimensions, shape and orientation of components, that will be used to assess the quality of the point cloud data. The patterns of deviations can be used to indicate the quality of a point cloud data and how much information is captured by the point cloud data. Synthesis of the studies in this field suggests that three major metrics can be used to characterize the information contained in point cloud data [14,22,23]. These are: (1) the point density, which defines the number of points within a unit area, (2) the uncertainty, which refers to the standard deviation of the shortest distance between points and the surfaces fitted to the points, and (3) the occlusion, which defines the regions of the object surface that have no corresponding points in the point cloud data. The point density determines the level of detail of the geometric information that a point cloud is able to provide for a given object. A high-density point cloud is capable of providing geometric information with greater details. The uncertainty is used to define the reliability of the measurements taken in a certain region within a point cloud. The uncertainty could be caused by noise in the data, edge losses (i.e., the mixed-pixels at the edge of two surfaces), low reflectivity of a surface, and irregularities of surfaces. The research presented in this paper extends these three concepts to quantify the geometric information of target building components captured within a point cloud data set.

2.2. Point cloud registration approaches

Multiple point cloud data sets can be combined together through the registration process. There are different registration approaches, which can be grouped into two classes: coarse registration and fine registration [24]. The coarse registration approaches align a set of point clouds using correspondences between each point cloud set. For instance, the corresponding points or targets can be manually selected from two point clouds (e.g., centroid of targets, markers), and the coarse registration approaches will align the set of point clouds in order to minimize the distances between the points selected from the point clouds. As a result, whether the selected point pairs are equivalent to each other or not will determine the accuracy of the final alignment.

The fine registration takes an entire point cloud data set into consideration [24–26] while registering different point clouds. Iterative closest point (ICP) is a well-known fine registration algorithm, which iteratively adjusts the alignment of a set of point clouds until the distances between points in one point cloud data and their closest points in the remaining sets are minimized [27,28]. The ICP algorithm is fully automated and no points need to be pre-selected for the registration purpose.

Registration errors are likely to be introduced into the combined data set when a pair of point clouds cannot be aligned perfectly. Hence, it is important to select a point cloud registration approach that has less registration errors when used to combine multiple point cloud data sets together. The performance of fine registration approach could be impacted by deformations that exist in point clouds, such as having appearances of building components change in progressively captured point clouds. On the contrary, the coarse registration done based on the equivalent targets is not influenced by the deformation between different point clouds. In this paper, we have captured a set of point cloud data for a research lab at different times during its renovation process. Due to the large spatial changes between point clouds captured at different times, it is quite challenging to use fine registration approaches to register the progressively captured point cloud together. Therefore, we placed targets in the scene during the scanning process to facilitate the scanning registration and used the equivalent target based coarse registration approach.

2.3. Scan planning approaches

Scan planning is a well-known problem in the computer vision domain. Specifically, the next-best-view (NBV) approaches focus on finding the minimum number of viewpoints, where a range sensor could be placed in order to scan all the surfaces of an object [29–31]. Various next-best-view (NBV) planning approaches have been developed in the computer vision domain to address the NBV problem [32]. These approaches are usually composed of two parts: (a) a method to represent and determine the visibility of an object surface from different viewpoints, and (b) a viewpoint selection algorithm that optimizes the coverage of sensors with the smallest number of views [32–36]. Various approaches have been used to represent the viewing volume of an object from a given viewpoint. Examples of such approaches include occupancy grids (or called as voxel grid), octrees and triangle meshes [37]. One of the commonly used representation approach is the occupancy grid, which encodes an object surface using a voxel grid. In a voxel grid, each voxel can be labeled as occupied (i.e., the voxel is captured by the scanner from a given viewpoint) or unoccupied. By counting the number of occupied voxels, the approach is capable of determining the coverage of a range image captured from a given location and orientation [34,38].

One of our research objectives is to develop an approach that selects a minimum number of point cloud sets captured at different times to provide a more complete set of geometric information for the BIM updating process. It is similar to the NBV planning approaches as they also target on finding a subset of point clouds or range images to cover all the target object surfaces. NBV planning approaches select range images captured at different viewpoints whereas the scanned objects remain the same during the scanning process. Hence, the changing variable of the NBV planning approaches is the location of the scanner. On the contrary, the approach developed in this research focuses on selecting a subset of point clouds captured at different times. The scanned objects might change among the scans captured at different times. As a result, the changing variable of the approach is time. However, the NBV planning approaches and the approach developed in this research share the same objective of increasing the coverage of scans and decreasing the redundant information by combining point clouds varies in location (NBV planning approaches) or in time (the approach developed in this research). Therefore, the NBV planning approaches provide a starting point for developing an approach to select and combine point clouds captured at different times. The visibility metrics (i.e., occupied/unoccupied) and the occupancy grids proposed in the NBV planning approaches are modified and used in the point cloud selection approach proposed in this paper.

3. Motivating case study: an analysis of completeness of geometric information in progressively captured point clouds

For a detailed analysis of completeness of geometric information contained in progressive point clouds, we conducted a case study while a research lab in a 100-year old university campus building was renovated. The renovated space was scanned from multiple locations to capture the interior of the research lab at six different times during the renovation process that went from May to August 2012. A pulsed time-of-flight (PTOF) scanner was used in the case study. The precision of the scanner is 2 mm and the maximum scan rate is 50,000 points per second. The lab layout and the scan locations are shown in Fig. 1. The color[1] of walls in the research lab is white.

In this analysis, we used the point clouds progressively captured at six different times at location 3 as the testbed. The six point clouds were captured at the same scanning location in order to eliminate the variances of geometric information caused by different scanning locations. These captured point clouds are referred to as P1, P2, P3, P4, P5 and P6 throughout the rest of this paper. To evaluate the geometric information contained in the progressively captured point clouds, we selected the ductworks installed in room 1 and analyzed how much information each point cloud is able to provide to update these ductworks in a BIM. The reason to use ductworks was that these ductworks were progressively installed during the renovation, and as a result point cloud data captured at different times has a high potential to provide different information regarding these ductworks. To update a ductwork segment manufactured in a rectangular shape, width, height and length of the segment need to be measured from a given point cloud data. The width, height and length of a ductwork segment are referred to as geometric properties of that ductwork segment. The analysis included 22 duct segments and their 66 geometric properties (i.e., width, height and length) that were measured in all of the six point clouds.

A geometric property can have three statuses in a point cloud:

- **Occluded**: Measurements from a given point cloud data are not possible as occlusions block the view of a component regarding that property.
- **Not installed**: Measurements from a given point cloud data are not possible as the corresponding component was not in place when the point clouds were captured.
- **Measurable**: Measurements from a given point cloud data are possible for the property being considered.

In this case study, targets were placed in the scene when laser scanning was progressively performed during the renovation process. A screenshot of targets presented in a point cloud is shown in Fig. 2. An equivalent target based point cloud registration approach was used to combine point clouds together. The six point clouds were progressively registered and analyzed for the status of the same 66 geometric properties shown in the registered point clouds. In total, five registered point cloud sets were generated, labeled as “P1 + P2”, “P1 to P3”, “P1 to P4”, “P1 to P5”, and “P1 to P6”.

Fig. 3 shows the status of geometric properties measured in the point clouds captured at a single point in time (i.e., P1, P2, etc.) as well as the progressively registered point clouds. In Fig. 3, each row represents a ductwork segment in the testbed. The blue, gray and black boxes represent whether a corresponding geometric property is measurable, not installed or occluded in the point cloud, respectively.

As shown in Fig. 3, when considered individually, none of the progressively captured point cloud sets is capable to provide a complete view for all the geometric properties for all these segments. In order to help interpretation of Fig. 3, screenshots of the analyzed duct segments taken from each of the six point cloud sets

[1] For interpretation of color in Figs. 1 and 3, the reader is referred to the web version of this article.

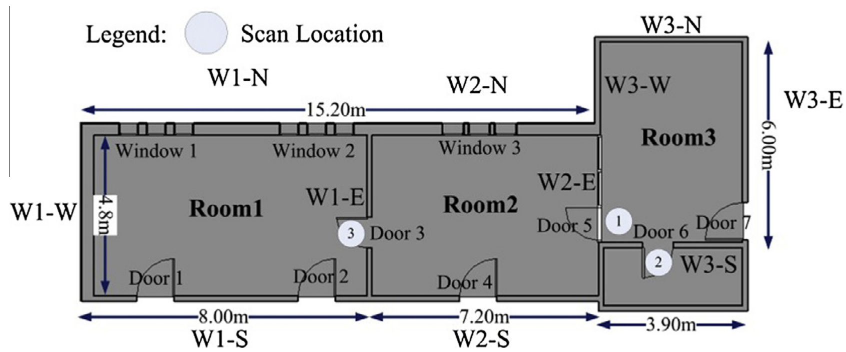

Fig. 1. Research lab site layout and the scan locations.

Fig. 2. Targets shown in a point cloud.

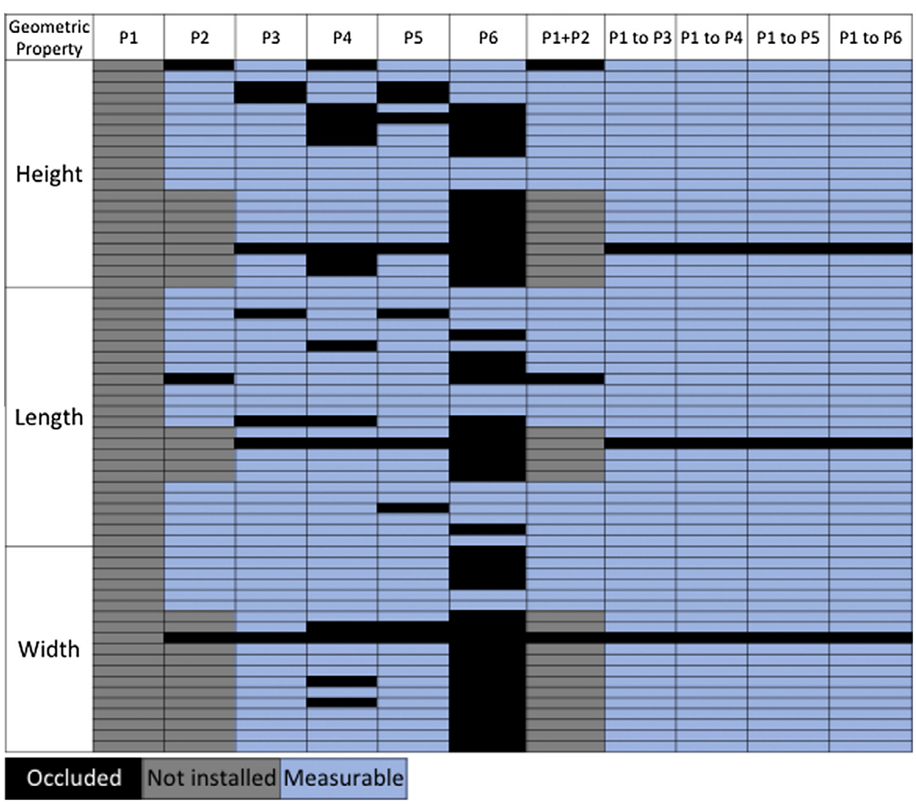

Fig. 3. Status of geometric properties captured by individual point clouds (P1, P2 ... P6) and the combination of them.

are shown in Fig. 4. Combining Fig. 3 with Fig. 4, it can be found that no ductwork segments were installed by the time P1 was captured, and thus all the 66 geometric properties are gray – hence have "not installed" status in P1. 42% of the geometric properties were "not installed" in P2. By the time P3 was captured, all the ductworks in Room 2 were installed (i.e., no segments with not-

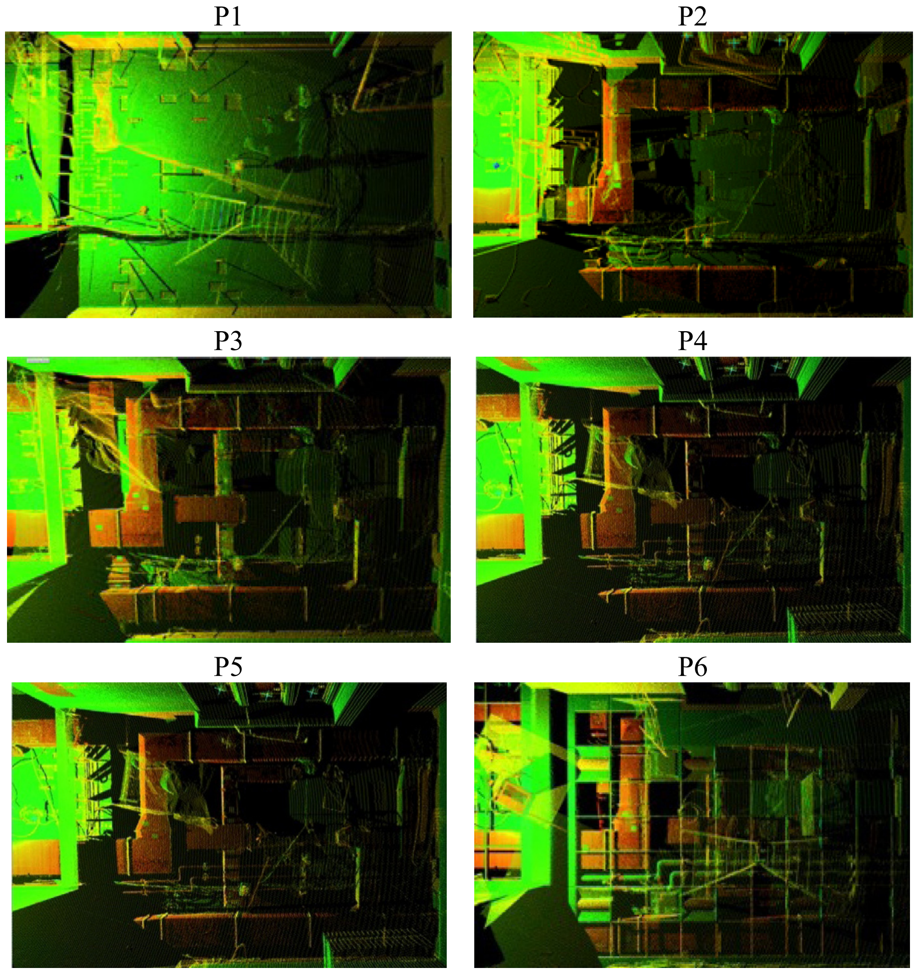

Fig. 4. Screenshots of the analyzed duct segments taken from each point cloud set.

installed status). Occlusions caused by temporary structures prevent a point cloud from capturing a complete view of target components and their associated geometric properties. In P3, 11% of the geometric properties were "occluded". 23% of the geometric properties captured by P4 were "occluded" and 14% of the geometric properties captured by P5 were "occluded". By the time P6 was captured, ceiling tiles and lighting fixtures were installed. They occluded most of the ductworks. As a result, the percentage of "occluded" geometric properties jumped to 67% in P6.

It was possible to extract more geometric properties from the merged point clouds than the point clouds captured at a single point in time. In the combined point clouds "P1 to P3", "P1 to P4", "P1 to P5" and "P1 to P6", 96% of the geometric properties were "measureable" and 4% of them were "occluded". The occluded geometric properties in the combined point clouds (shown as black boxes in Fig. 3) were either "occluded" or "not installed" in all of the six progressively captured point clouds.

An important observation was that when point cloud data P1 to P3 are combined, this data set provided the same number of geometric properties as compared to combining all six point cloud sets together. Adding P4, P5 and P6 into the registered point cloud did not increase the number of "measurable" geometric properties for the analyzed duct segments. It shows that combining more point cloud sets does not always mean that the registered point clouds would provide more geometric properties in relation to the target components.

In addition, as observed from Figs. 3 and 4, the occlusions are randomly distributed in the six point clouds. However, as renovation progresses, it is likely that the probability of having the same occlusions occurring at exactly the same locations will decrease. It will be possible to get measurements in the point cloud data captured later in time for the geometric properties that were "occluded" or "not installed" in the point cloud data captured earlier in time. As a result, when multiple progressively captured point clouds are combined together, it is possible to retrieve geometric properties that were occluded or not installed in other point clouds.

However, the increase in the number of measurable geometric properties provided by a combined point cloud data set is not proportional to the increase in the number of point cloud data sets that are combined together. Adding more point cloud data sets will increase the size of the final data set though it might not always provide additional measurable geometric properties. Given the large file size of a point cloud data, combining multiple point clouds together would generate a combined point cloud that requests a large storage space and processing time. For instance, six point clouds were collected at different points in time in the motivating case study, and the average size of a file containing one set of point cloud data was around 320 MB. Combining these six point cloud data sets together generated a 2 GB file that contains 13 million points for just one scan location. In a case study done at Carnegie Mellon University on a two story building construction site, a total of 68 scans were conducted to capture the indoor and outdoor environments of a 38,000 square foot building in just one visit. If we progressively scan the building and combine the scan data all together at different times it will generate a large

Please cite this article in press as: T. Gao et al., An approach to combine progressively captured point clouds for BIM update, Adv. Eng. Informat. (2015), http://dx.doi.org/10.1016/j.aei.2015.08.005

data set that is difficult to store, manipulate and process [4,39,40]. Therefore, having a pre-selected set of point clouds could reduce the size of final point cloud data and also potentially improve the usage for the final point cloud data. In order to support the decision of which point clouds to be registered, there is a need to develop an approach to evaluate the geometric information contained in each point cloud set and assess the gained information when additional point clouds are registered together. The next section provides the details of the point cloud selection approach developed for this purpose.

4. An approach to evaluate information contained in progressively captured point clouds and select point clouds to be combined

This section introduces the point cloud selection approach developed in this research. The approach assumes that an as-designed BIM is available and progressive laser scans are captured on the site. The consideration of the quality of laser scan data is not within the scope of this paper. The approach is composed of two modules: (1) content assessment module, which quantifies the geometric information contained in each point cloud data for updating/modeling target building components in a BIM, and (2) content improvement module, which calculates the information gained by adding one point cloud data to another. This module requires the output of content assessment module. Each module is detailed in the following subsections.

4.1. Content assessment module for quantifying the geometric information contained in a point cloud

Fig. 5 shows the flowchart of the content assessment module. The content assessment module takes two inputs: a set of point cloud data captured at different points in time and a set of target components modeled in the BIM. For selected surfaces associated with the target components, this module applies a grid-based evaluation approach to quantify the geometric information provided by a point cloud data set. For each surface of a target component, the grid-based approach overlays a grid on the surface of a target component and divides the target surface into a finite number of cells. The grid-based point cloud evaluation approach can be divided into two steps: (1) grid construction and (2) point cloud geometric information assessment, as detailed below:

Step 1: Grid construction

Grid construction step overlays a grid onto each surface of targeted components modeled in a BIM. The grid divides a given surface of target components into a finite number of cells. The size of a cell is determined based on the size of the surfaces and the level of detail required by the assessment conducted in the next step. As an example, Fig. 6a shows a grid that is generated over a surface of ductworks modeled in a BIM, which divides the surface into a number of cells with the size of 0.04 m.

Step 2: Point cloud geometric information assessment

This step analyzes a point cloud using the same grid generated in Step 1 for each surface of the components modeled in a BIM. During this step, first the point cloud and the BIM are aligned into the same coordinate system using the ICP algorithm, so that the grid can also be aligned with the point cloud. The initial alignment between the point cloud and the BIM was made manually by aligning corresponding points in the two data sources. After the grid is overlaid with the point cloud, each cell in the grid contains a set of points. When a cell does not contain any points, the geometric information is missing in this cell. There are several reasons for the missing points in a cell, such as: (a) corresponding building surface could be occluded, (b) corresponding building surface could still be not installed when the point cloud data was captured, and (c) the reflectivity of the corresponding building surface, which results in having no laser beam being reflected and returned back to the scanner.

To easily differentiate cells with points and without points, a coverage image is generated in this step, which uses a color-coding to indicate whether a cell contains any information related to target surfaces or not. Fig. 6a shows a screenshot of ductworks modeled in the BIM and the grids overlapped on top of the

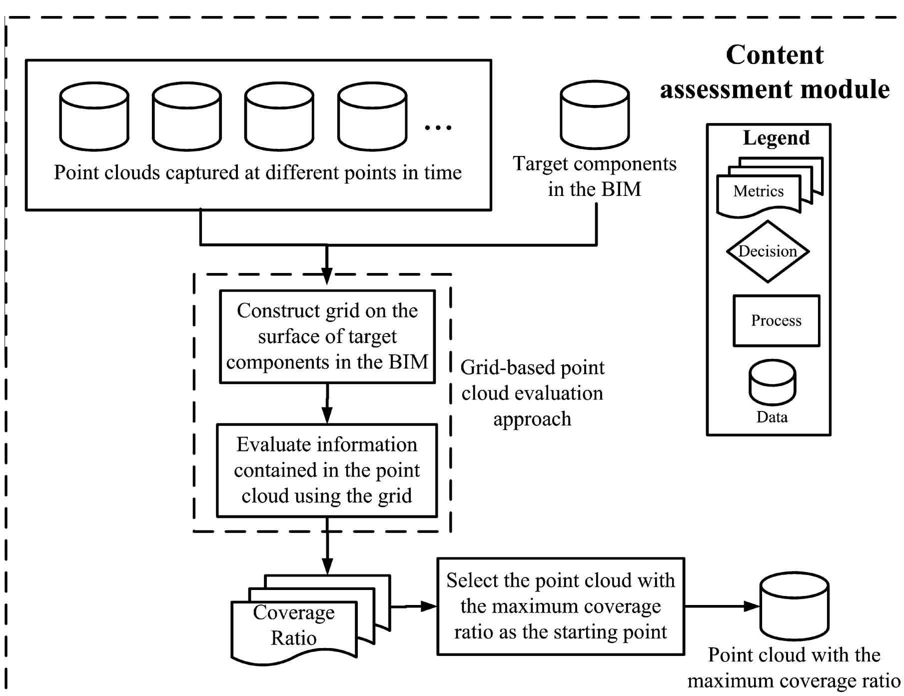

Fig. 5. The flowchart of content assessment module.

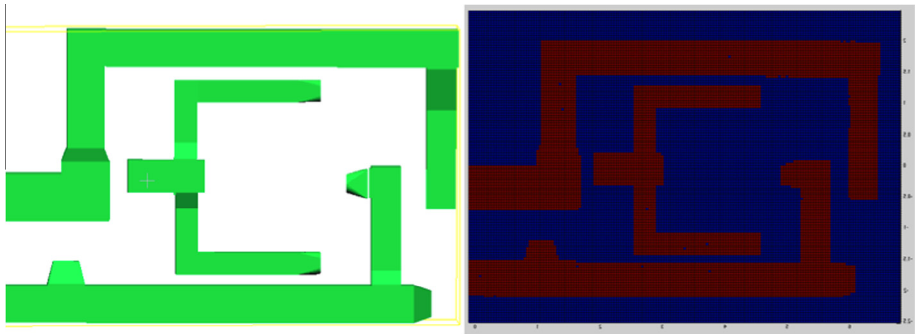

Fig. 6a. Ductworks modeled in a BIM and the grid overlaid on the surfaces of ductworks (red cells are the cells occupied by the model, cell size is set as 0.04 m). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

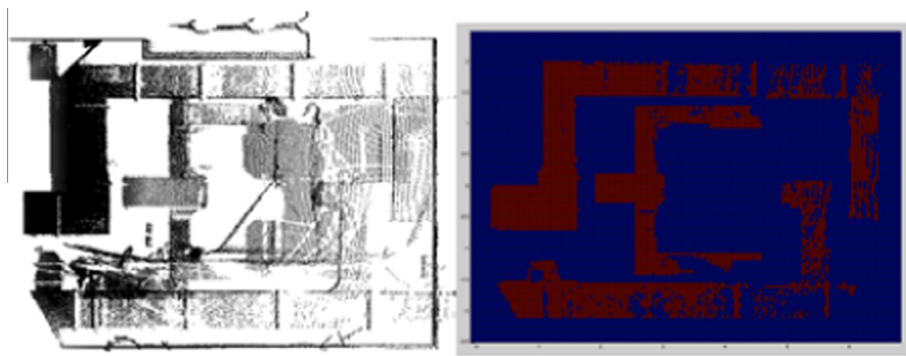

Fig. 6b. Ductworks captured by a point cloud (left) and the coverage image (right), where the red cells indicate that the cells contain the points associated with the target surface (cell size is set as 0.04 m). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

ductwork surfaces. Fig. 6b shows a point cloud data and its coverage image. The coverage image is used to quantify the information contained in each grid using a metric called, the *coverage ratio*. The coverage ratio refers to the ratio of a surface that is clearly presented in a point cloud without any occlusions over the entire surface and is calculated for each surface using the equation given below:

$$\text{Coverage ratio} = \frac{\text{number of cells occupied on the grid overlaid on a point cloud for a surface}}{\text{total number of cells available on the grid for that surface}} \tag{1}$$

A cell is occupied if there is a point inside that cell. A low coverage ratio means that a given point cloud set cannot provide enough geometric information to model/update target surfaces. It also suggests that additional point clouds need to be added in order to cover the missing portion of the components for accurate measurements.

Step 2 is repeated for all the surfaces of a given component and for all the point cloud sets. The content assessment module calculates the coverage ratio of all the input point cloud data sets for the targeted surfaces in the BIM. The point cloud with the maximum coverage ratio is the one that is capable of providing the most complete geometric information for the specific surfaces of the target components and is marked as the baseline point cloud.

To better demonstrate how the content assessment module works, we used four point cloud data sets captured at four different times as an example, and selected the ductworks shown in the point clouds as the target building components. Fig. 7 shows four point clouds captured at different points in time and their coverage images for the shown surfaces of the ductworks. According to the coverage ratios, P3 has the highest coverage ratio as 67.6% for the surfaces of ductworks and hence should be used as the baseline point cloud. The remaining point clouds need to be evaluated in order to determine which point clouds should be combined with the baseline point cloud data. This ties to the second module, which is the content improvement module.

4.2. Content improvement module: assessing the information gain by combining additional point clouds

This module takes the baseline point cloud identified by the content assessment model as an input together with the remaining sets of point cloud data, and determines which remaining point clouds should be combined with the baseline point cloud for the target surfaces and their geometric properties. The flowchart of this process is shown in Fig. 8.

This module assumes that there is n number of sets of point cloud data ($P_1, P_2, P_3 \ldots P_n$), and P_j is selected as the baseline point cloud data with the highest coverage ratio among n number of point cloud data. This module first compares each of the remaining point clouds to the baseline point cloud, and calculates how much information can be gained for the target geometric properties, by adding each of the remaining point cloud data into P_j individually. When comparing P_i $(1 < i \leqslant n)$ with the baseline point cloud – P_j, the module utilizes the same grid generated in the content assessment module and overlays the coverage images of P_j and P_i together. The content improvement module then examines the coverage images and identifies the cells that are occupied by P_i, but not by P_j. These cells refer to the target surface areas that were

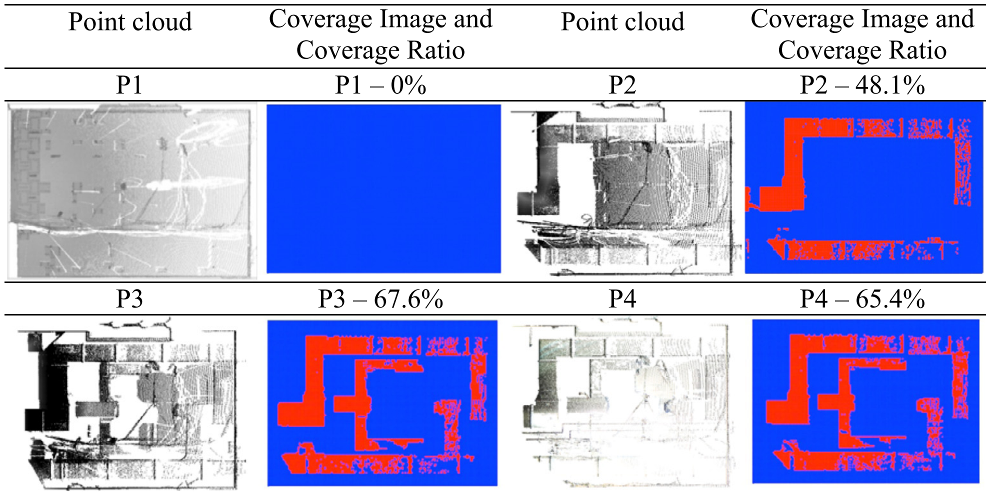

Fig. 7. Point cloud data captured at different points in time and their occlusion images for duct segments.

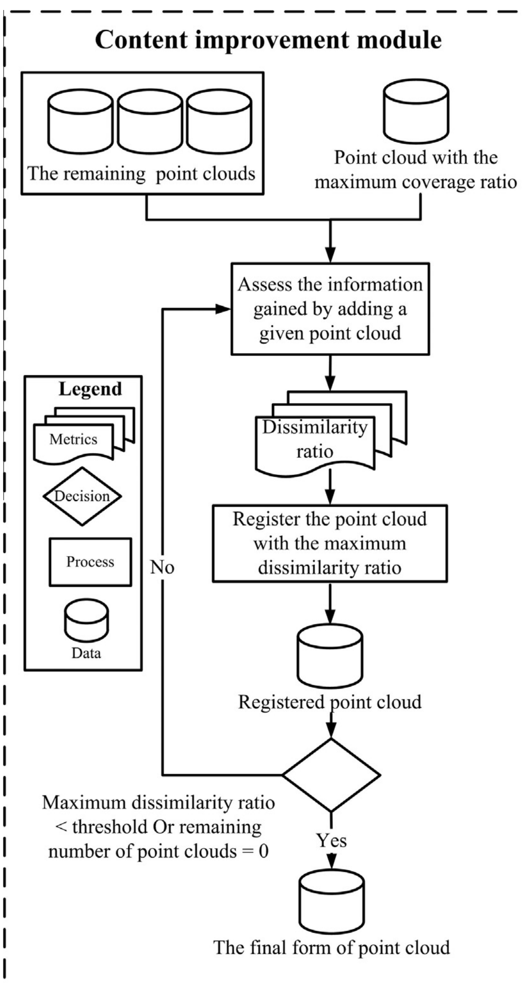

Fig. 8. Flowchart of the content improvement module.

shown in P_i, but could not be captured or were occluded in P_j. To quantify this additional geometric information, a metric, named as *dissimilarity ratio*, has been introduced. The dissimilarity ratio represents the percentage of information gained by adding the new point cloud into the baseline point cloud, and is calculated using the following equation:

$$\text{Dissimilarity ratio } (P_i, P_j) = \frac{\text{number of cells occupied in } P_i \text{ but not } P_j \text{ on a given surface}}{\text{total number of cells available on the grid on a given surface}} \quad (2)$$

where P_i is the baseline point cloud.

Fig. 9 shows the result of the assessment for the same set of ductworks used as an example in the previous module. The additional information generated by adding P2 into the P1 is shown in the third column.

This assessment is repeated until all the point clouds at hand are compared to the baseline point cloud. The point cloud with the maximum dissimilarity ratio is defined as the one that has the highest information to add to the baseline point cloud. This point cloud is then registered with the baseline point cloud and considered as the new baseline point cloud for the next iteration. The model iteratively combines the remaining point clouds to the baseline point cloud till either all the point clouds have been registered together or the maximum dissimilarity ratio is smaller than a threshold, whichever occurs earlier. Users determine the value of the threshold. If the dissimilarity ratio of a point cloud is smaller than the threshold, it is not worth adding this point cloud to the baseline point cloud set since the combination will increase the file size without bringing enough additional geometric information for the model update/construction. The output of the content improvement module is a point cloud that is composed of the selected point clouds.

5. Validation

We validated the performance of the developed approach in terms of whether the approach is able to identify the right combination of point clouds in order to get a more complete set of geometric information with less file size. In order to evaluate the efficiency of the developed approach, its performance has been compared with two other approaches (i.e., approach 1 and approach 2). In approach 1, all the point clouds are registered together. In approach 2, the point clouds are progressively registered, in the order that they were acquired, until the dissimilarity ratio reaches to a preset threshold, which is the same threshold used in the developed approach. The approach developed in this research (i.e., approach 3), however, first uses the coverage ratios to select the baseline point cloud and then determines which point clouds should be combined with the baseline point cloud using the

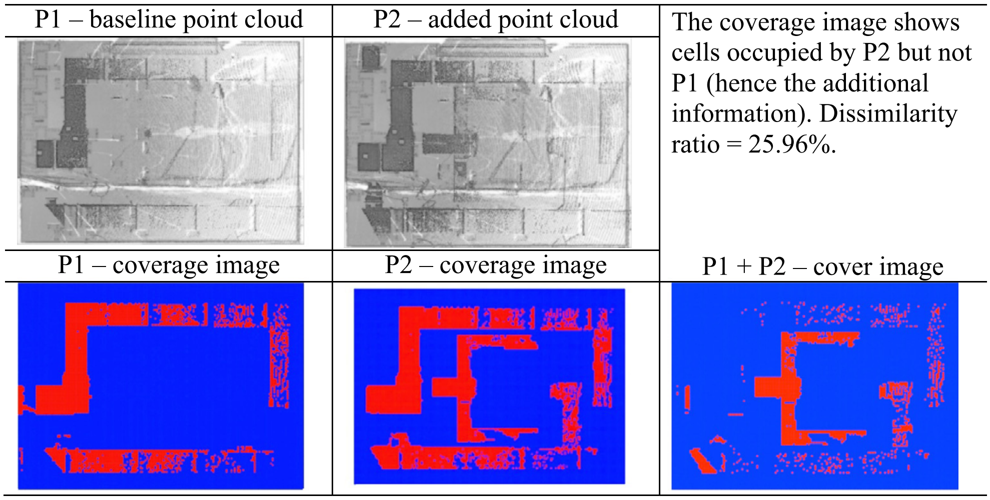

Fig. 9. Dissimilarity ratios by adding P2 to P1, where P1 represents the baseline point cloud data.

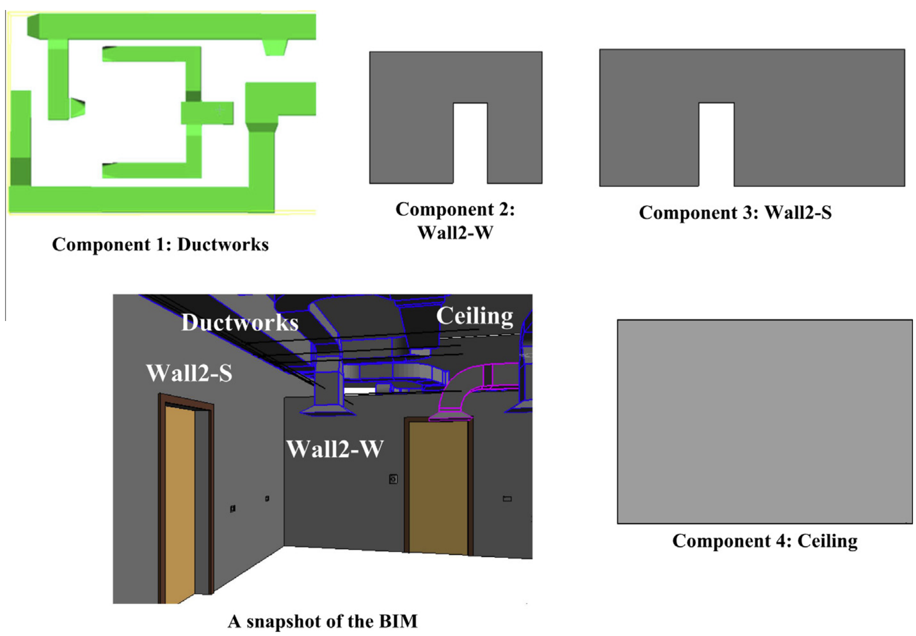

Fig. 10. A snapshot from the model that captures all the component types used in the validation.

dissimilarity ratios. The combined point clouds generated by the three approaches were compared. Three metrics were used in the validation, as: (a) the coverage ratio, (b) the number of geometric properties that can be measured in a baseline point cloud for target surfaces of components, and (c) the size of the final point cloud file merged.

The validation data includes five sets of point cloud data progressively captured during the renovation of the research lab, as detailed earlier in the paper and labeled as (P_1, P_2, P_3, P_4, and P_5). We focused on three different types of building components, which are (1) duct segments: surfaces of segments installed in room 2, (2) interior walls: surfaces of Wall2-W (i.e., western wall in room 2), and Wall2-S (i.e., southern wall in room 2), and (3) ceilings: the surface of ceiling in the room. A set of screen shots of the components used in the validation is shown in Fig. 10. These components were selected to ensure that the approach can be generalized to different types of building components.

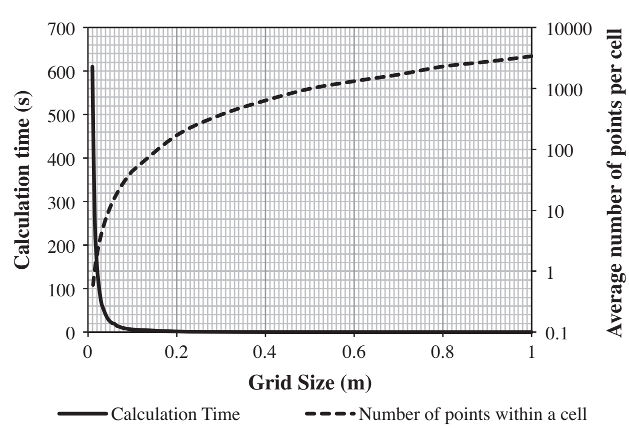

Fig. 11a. Processing time and point cloud density vs. grid.

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Table 1
The resulting subset of point clouds to be registered following the three approaches.

Approach	Component 1: Ductworks	Component 2: Wall2-W	Component 3: Wall2-S	Component 4: Ceiling
1	P1 + P2 + P3 + P4 + P5	P1 + P2 + P3 + P4 + P5	P1 + P2 + P3 + P4 + P5	P1 + P2 + P3 + P4 + P5
2	P1 + P2 + P3	P1 + P2 + P3 + P4	P1 + P2 + P3	P1 + P2 + P3 + P4
3	P3 + P4	P4 + P1 + P2	P1 + P3	P1 + P2 + P5

Table 2
Comparison of the developed approach (approach 3) with respect to other baseline approaches.

Approach	Component 1: Ductworks			Component 2: Wall2-W			Component 3: Wall2-S			Component 4: Ceiling		
	C	M	S	C	M	S	C	M	S	C	M	S
1	75.7%	41	11.2	92.5%	4	11.2	94.0%	4	11.2	96.5%	4	11.2
2	74.0%	41	6.9	92.1%	4	9.2	93.9%	4	6.9	96.5%	4	9.2
3[a]	75.0%	41	4.5	90.8%	4	7	93.7%	4	4.6	96.5%	4	6.7

C: coverage ratio M: number of measurable geometric properties S: number of points (million)

[a] Shows the developed approach.

Each approach of selecting point clouds for complete geometric information for model updating process has been implemented in Matlab and tested using the validation data. The resulting selections of point clouds to be registered following the three approaches are shown in Table 1. $P_i + P_j + \cdots + P_k$ shown in Table 1 indicates that point cloud $P_i, P_j, \ldots, P_k$ are combined in the stated order. The point clouds are merged in their entirety and they are not pre-segmented based on the target-building component. If the point clouds are pre-segmented based on the surface of interest, the same approach can be applied to select the least number of point cloud segments for each surface of interest.

The comparison of the results using the metrics defined earlier is provided in Table 2. Table 2 shows that the coverage ratio increases when additional point clouds are added into the baseline point cloud. At the same time, the rate of growth of the coverage ratio decreases. The geometric properties remain the same in the combined point clouds generated by the three approaches. The developed approach (approach 3) achieved the point cloud with smallest number of points and smallest file size in all of the four validation datasets by suggesting the least number of point cloud data to be merged.

For the ductworks, the coverage ratio of the registered point clouds generated by approach 1 is 2.3% higher than the registered point clouds generated by approach 2. However, the number of points of the final point cloud generated by approach 1 is 62.3% higher than approach 2. It shows that when registering all of the point clouds together without any pre-selection, the increase of file size might overweight the improvement in relation to the completeness of the geometric information. For the interior surface of Wall 2-W, the combined point cloud gained by approach 3 has the coverage ratio as 90.8%. Approach 2 added one more point cloud into the registered point cloud, which increases the coverage ratio by 1.5%, but also increases the number of points by 31.4%. Approach 1 combined all the point clouds together. This approach increases the coverage ratio by 2% and the number of points by 60%, as compared to the third approach. We also counted the geometric properties that can be measured from the point clouds. The geometric properties for the analyzed building components include length and width of the building surfaces. The measurable properties remain the same for the studied building components and for the implemented approaches. The result showed that using approach 3, it is possible to reduce the number of point clouds that need to be registered so as to reduce the file size. As shown in Table 2, as compared to the other two baseline approaches, we can retrieve more geometric information (i.e., higher coverage ratio) using the least number of point clouds (i.e., less number of points and less file size), which validates the effectiveness of our approach.

Two factors play a role in the performance of the developed approach: the grid resolution and the threshold values. The selection of the grid size would change the value of the coverage ratio. The coverage ratio is an estimate of how much geometric information is provided by a point cloud data set and the size of a cell will influence how many points (if any) fall in each cell. Hence, it is important to balance the grid size. When the grid size is too large, the coverage ratio might only provide a rough estimate for the geometric information contained in a point cloud data set. On the other hand, when the grid size is too small, the coverage ratio will be too sensitive to the noises presented in a point cloud and will take more time to compute.

We have performed sensitivity analysis of grid size on the performance of the approach. Fig. 11 shows the sensitivity results of incrementally changing the grid size from 0.01 m to 1 m, and resulting coverage ratios for the surfaces of duct segments shown in Fig. 6. In addition, we also recorded the calculation time for each of the grid size and calculated the average number of points that belonged to a point cloud within a cell. The sensitivity analysis was conducted on a 64 bit computing platform with i7 2.4 GHz CPU, 8 GB RAM and SSD hard drive. Fig. 11a shows the resulting calculation time and the average number of points within a cell when the grid size is changing from 0 to 1. As seen in Fig. 11a, the calculation time increases while the grid size decreases. When the grid size decreases from 0.1 m to 0.01 m, the calculation time increases significantly. When the grid size is equal to 0.01 m, the calculation time is 100 times greater than the calculation time when the grid size is 0.01 m. In the meantime, the average number of points per cell decreases along with the decrease of the grid size. Having too many points within a cell could indicate that the grid based evaluation approach can only provide a rough estimate for the geometric information contained in a point cloud. Decreasing the grid size would result in a more accurate estimation for the geometric information contained in a point cloud data, but it would also increase the calculation time significantly. A good selection of the grid size needs to balance the calculation time and the average number of points per cell. Fig. 11b shows the relationships between the grid size and the coverage ratio. As shown in this figure, dividing a building surface with a large grid size could lead to an overestimate for the information contained in a point cloud. In the validation section, we selected the grid size as 0.04 m since it provides a good balance between calculation time

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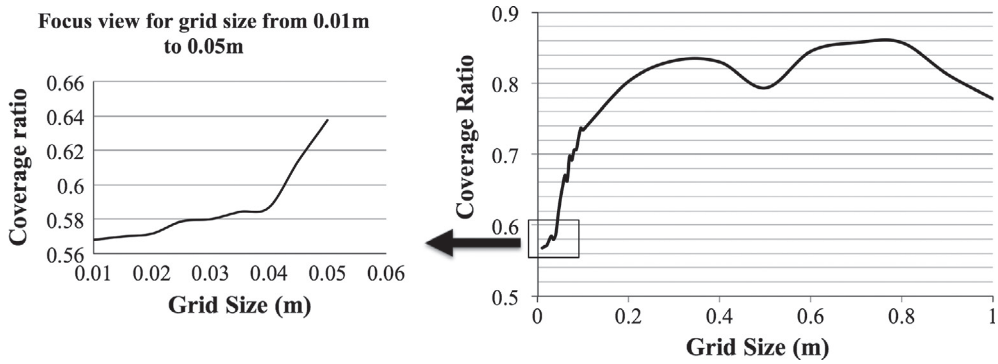

Fig. 11b. Coverage ratio vs. grid size.

and estimation accuracy for our specific case. As shown in Fig. 11, the coverage ratio becomes more and more stable after decreasing below 0.04 m while the calculation time is increasing rapidly. For instance, when the coverage is changed from 0.04 m to 0.01 m, the coverage ratio only decreases by 3% whereas the calculation time increased by 14 times. One thing worth to notice is that users might have different computing resources or preferences for the calculation time and the estimation accuracy. Hence the grid size selected in this paper is not necessarily to be the optimal solution.

In the validation calculations, the threshold was set as 1% for all the datasets. The value of threshold also impacts the performance of the developed approach. When threshold is set as 0, approach 1, 2, and 3 gave the same result, since they all combine all of the point clouds together. When the threshold value is increased, it means that the size of the registered point cloud has gained more weight. As a result, less number of point clouds will be combined together. The impacts of the threshold on the developed approach and the selection of the optimal threshold will be addressed in the future work.

6. Conclusion

Progressively captured and registered point clouds provide opportunities to capture a more complete view of the building components over time. A unique challenge of using registered point clouds is that registering point clouds that contain overlapping information might increase the difficulty of storing and processing registered point clouds due to file size. This paper presented an approach that evaluates the information contained in point clouds and supports the decision on which point clouds should be combined. Instead of registering all the point clouds together, the approach only combines the point clouds that contain less repetitive geometric information, which effectively reduces the file size of the final dataset and increases the usability of the data. Base on our validation experiment, the approach represented in this paper is capable of retrieve more geometric information (i.e., higher coverage ratio) using the least number of point clouds (i.e., less file size). Hence, our approach allows construction professionals to rapidly evaluate the information contained in progressive point clouds and selectively combine progressive captured point clouds to provide a complete set of geometric information with reduced file sizes for the BIM update.

There are several limitations of the approach presented in this paper, which are worthy of future research. First, in this paper, we used a 4-month renovation project as the testbed to test and validate the developed point cloud selection approach. In the future research, it would be interesting to test the performance of the approach presented in a building environment where different types of building components, temporary components and noises co-exist and evaluate how the approach would perform under those conditions. Second, the coverage ratio is calculated over 3D planes where a grid can be constructed. There is a potential to extend the grid construction method and calculate the coverage ratio for more complex surfaces, such as cylinders or NURBs surfaces. A 3D surface can be represented by a set of connected polygons (e.g., triangles) using polygonal modeling approach. In the future research study, it would be possible to represent 3D surfaces as a set of polygons and overlay a point cloud with those polygons. The coverage ratio can then be calculated as the number of occupied polygons divided by the total number of polygons. Third, the approach presented in this paper treats all the surface areas equally. However, information contained in different surface areas might vary based on the location. For instance, edges might contain more information than center areas in some cases. An important future research study would be to assess how the suggested registration options would change based on assigning different weights to different surface segments. Combining that with the techniques, such as edge detection or surface reconstruction, it would be possible to retrieve sufficient information for model update/construction with point clouds where only partial surfaces are captured. Fourth, the differences between an as-designed BIM and the actual building condition might cause an inaccurate estimation of the coverage ratio. A research study has been done by the authors that focus on developing algorithms to match components of an as-designed BIM to segments extracted from point clouds under different discrepancy conditions (e.g., an ductwork modeled in the BIM is constructed at different location with different shapes and sizes) [41]. There are also other approaches that could be used for such mapping process. For instance, Bosche developed an approach that converts a BIM into a virtual point cloud and then matches points of the virtual point cloud to points from the actual point cloud [42]. In the future research study, it would be possible utilize these matching algorithms to identify the matches between a point cloud and an as-designed BIM and adjust the impacts of BIM-point cloud variations on the calculation of the coverage ratio.

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