Point-to-point Comparison Method for Automated Scan-vs-BIM Deviation Detection

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Abstract:
Laser scanning is one of the most accurate methods of measuring the geometric accuracy of the as-built condition of a construction site. However, using laser-scanned point clouds for the purpose of measuring the deviation between the as-built structures and the as-planned Building Information Model (BIM) remains cumbersome due to the difficulty in registration, segmentation, and matching of large-scale point clouds. Conventional methods for automated deviation detection are computationally intensive and only work for regular geometric shapes such as planes and cylinders. This research proposes a point-to-point comparison method for automated scan-vs-BIM deviation detection. First, a laser-scanned point cloud is collected and imported into a BIM file. A column-detection routine is used to locate the centroid of each column in the x-y plane for both the BIM and point cloud data. The Random Sample Consensus (RANSAC) method is used to determine the optimal translation and rotation parameters to register the BIM and point cloud data. Next, the BIM model is converted to point cloud format by uniformly sampling points from each face of the building mesh model. The laser-scanned point cloud is similarly down-sampled to be at the same resolution as the BIM-derived point cloud. A point-to-point comparison sequence is carried out to measure the deviation of building elements between the BIM and laser-scanned point clouds. Regions in the point cloud are highlighted according to the degree of deviation to alert the user to the areas that require further inspection. Experiments were carried out using laser-scanned point clouds of an indoor hallway to validate the proposed approach. Results show that the proposed column-based registration method achieved a translation error rate of 0.15 meters and a rotation error rate of 0.068 degrees. The computation time required is 3 seconds for the column-based registration step and 70 seconds for the deviation detection step. The main contribution of this research is to propose a non-parametric, class-agnostic approach to deviation detection in order to handle the variation in the geometric shape of different building elements.

Keywords: Laser scanning; point cloud; Building Information Modeling; object detection; deviation detection

1. INTRODUCTION

Building Information Modeling (BIM) is widely used to design and manage construction projects by representing and sharing information about building assets. The as-built BIM may be used for various construction management applications such as quality control (Anil et al. 2013), progress estimation (Golparvar-Fard et al. 2009; Kim et al. 2013), asset management (Son et al. 2015), and safety planning (Kim et al. 2016). Due to human error, however, discrepancies often occur between as-built and as-planned conditions of building elements such as pipes, conduit, and ductwork (Bosché et al. 2015). Accurate assessment of these discrepancies is important for timely progress checking and quality control on construction sites. Revisions to the as-planned BIM need to be carried out in the event of design changes or construction errors that occur during the construction phase (Son and Kim 2017). Knowledge of the object deviations from planned models would allow the management team to refine the construction progress measurement and perform appropriate schedule updates (Son et al. 2017). The as-is infrastructure may also deviate from as-designed conditions due to the aging process. In such cases, the laser-scanned point cloud may be reconstructed into finite elements models (FEM) to perform structural health monitoring (Yan et al. 2017).

In a conventional Scan-to-BIM pipeline, the point cloud data collected from a jobsite is first converted into a BIM format before further additional analysis is carried out (Chen et al. 2017, 2018). However, this conversion process is often performed manually which contributes to increased labor hours, vulnerability to errors, and reduced efficiency (Hajian and Becerik-Gerber 2010). In addition, confounding factors such as point cloud quality, completeness, and level of detail (LOD) may lead to unreliable object recognition results (Rebolj et al. 2017).

Bosché (Bosché et al. 2015) first proposed the automated retrieval of building structural components by matching field-acquired point clouds to 3D Computer Aided Design (CAD) models. The Iterative Closest Point (ICP) technique was used to register point cloud objects with their corresponding CAD models and
produce a position estimate for targeted structural components. This process allows engineers to compare the as-designed versus as-built state of the construction site for progress tracking and clash detection purposes. However, the method required a supervised step to obtain the initial coarse registration. Nahangi and Haas (2014) also used the ICP algorithm to register as-built and as-planned pipe spools while using the Root Mean-Squared Error (RMSE) to quantify the degree of deviation. However, the study focused only on angular deviations and not translational deviations.

The Scan-vs-BIM method was also investigated for the case of detecting cylindrical Mechanical, Electrical and Plumbing (MEP) components and computing the “percentage built as planned” metric (Boscé et al. 2015). The combination of a Hough transform-based circular cross-section detection and registration with as-planned BIM allowed the method to handle out-of-plane deviations and pipe occlusions. The method worked well but is applied specifically to objects with known geometric shape (e.g., cylinders).

The application of Scan-vs-BIM was further extended by Turkan et al. to create a 3D object-oriented construction progress tracking system with schedule information (Turkan et al. 2012) as well as tracking secondary and temporary structures (Turkan et al. 2014). The user selects a few input parameters to register the point cloud and perform surface-based object recognition. One finding of the study was that visibility issues in the data led to imprecise progress estimates.

Kalasapudi et al. (2017) successfully improved the existing data-model comparison methods by integrating nearest neighbor searching and relational graph based matching into a single approach. The combined approach is able to handle objects packed in small spaces and minimize object mismatches while maintaining computational efficiency with respect to the number of building elements. However, the initial Constrained Iterative Closest Point registration still required users to manually align larger ducts. Bueno et al. (2018) used the idea of 4-plane congruent sets to register point clouds with a building model. The method proved to be effective in building construction environments which consist of multiple planar elements. However, user input is still required to pick the correct transformation in difficult cases involving symmetries and self-similarities.

In summary, the conventional methods for site quality control still lack robustness with respect to the registration step as well as the type of targeted building elements. Thus, this research proposes the use of an automated column-based registration procedure coupled with a point-to-point comparison method for automated scan-vs-BIM deviation detection. The method represents a non-parametric, class-agnostic approach to deviation detection in order to handle the variation in the geometric shape of different building elements. The rest of this paper will present the methodology, results, and discussion.

2. METHOD

The proposed method for scan-vs-BIM deviation detection consists of four main steps: (i) column detection in the laser-scanned point cloud, (ii) column detection from the as-planned BIM model, (iii) column-based scan registration, and (iv) point-to-point deviation detection. Each step will be discussed in detail below:

2.1 Column Detection in Point Cloud

The laser-scanned point cloud and the as-planned BIM model are initially misaligned because the data are collected in different coordinate systems. The two models have to be registered together in the same coordinate system in order to directly compare their geometry. Columns are selected to be the basis for registration because they are built in the initial stage of building construction the centroid can be easily determined from geometric data. To detect columns in the point cloud, it is first projected onto a 2D height map, \( H(x,y) \), which records the height occupancy from floor to ceiling at each discrete 2D location \((x,y)\). Next, a rule-based detection scheme is applied where each \((x,y)\) cell is classified as belonging to a column element if the height map value at that location exceeds 40% of the maximum height map value (Equation 1). At this stage, each actual column may be detected as multiple entities because the presence of a column can lead to high values in any proximate \((x,y)\) locations in the height map. Thus, a clustering technique is used where neighboring columns within 0.7m of each other will be grouped into a single detection. This step assumes that the centroid of two different columns will not be closer than 0.7m. Also, this tolerance can be flexibly adjusted per different columns-spacing building’s structural designs.

\[
I_{s\_column}(x,y) = \begin{cases} 
1, & H(x,y) > 0.4 \max_{(x',y')} H(x',y') \\
0, & \text{otherwise}
\end{cases}
\]  

(Equation 1)
2.2 Column Detection in BIM Model

Columns in the BIM model may be directly retrieved by selecting BIM elements with the column label. However, in the case where labels are unavailable, the columns may still be detected by first converting the BIM model into point cloud format and applying Step 2.1 above. Figure 1 shows a 2D visualization of the column centroids detected in the laser scan (annotated as crosses), overlaid with the column centroids in the as-planned BIM model (annotated as circles). Note that the set of Lidar columns may be greater than the set of BIM columns, due to the fact that outliers occur when miscellaneous clutter in the real construction environment are mistakenly detected as columns.

![Figure 1. Column locations detected in the laser scan and in the BIM before registration](image)

2.3 Column-based Scan Registration

The RANSAC algorithm (Fischler and Bolles 1981) is used to estimate the optimal transformation parameters that would align the laser scans with a given BIM model, a process also known as registration. The RANSAC procedure is carried out iteratively for 10000 steps. At the start of each iteration, two columns are randomly sampled from each of the input point clouds. Given two column centroids, \( p_1 \) and \( p_2 \) from the Lidar-generated point cloud and two column centroids, \( q_1 \) and \( q_2 \), the optimal translation parameters, \( T_x \) and \( T_y \) and the optimal rotation parameter, \( \theta \), can be calculated using Equations 2 - 4. Next, the entire set of columns from the Lidar point cloud is transformed, and the alignment is scored based on the number of correctly placed columns (within the threshold of 0.5m). The optimal parameters are updated at the end of every iteration if a more accurate alignment is found. Figure 2 shows the alignment of Lidar columns and BIM columns at the end of the registration step. Even though there are many outliers in the Lidar dataset due to false detections, the RANSAC algorithm is able to account for this by only sampling a minimum of two columns each time, and only keeping results that have high inlier rates.

\[
\theta = \tan^{-1}\left(\frac{(q_2(y) - q_1(y))(p_2(x) - p_1(x)) - (p_2(y) - p_1(y))}{(q_2(y) - q_1(y))(p_2(x) - p_1(x)) - (p_2(x) - p_1(x))}\right) \tag{Equation 2}
\]

\[
T_x = q_1(x) - p_1(x) \cos \theta + p_1(y) \sin \theta \tag{Equation 3}
\]

\[
T_y = q_1(y) - p_1(x) \sin \theta - p_1(y) \cos \theta \tag{Equation 4}
\]
2.4 Point-to-point Deviation Detection

Once the two datasets are properly aligned, the deviation of individual elements may be measured. In order to directly compare laser-scanned site data, which is usually in point cloud format, and as-planned BIM data, which is usually in mesh format, a synthetic point cloud is generated from as-planned BIM. The synthetic point cloud is generated by the following steps: for each triangle in the object mesh model (i) calculate the area of the triangle, (ii) calculate the number of points, \( N \) to be sampled based on a sampling density of 50 points per \( \text{m}^2 \), (iii) pick \( N \) points within the triangle and add them to the point cloud. Next, the laser-scanned point cloud is downsampled into a voxel grid with resolution, \( \lambda = 0.2\text{m} \). Each voxel can either be in an “occupied” or “unoccupied” state based on the rule in Equation 5. The synthetic point cloud generated from as-planned BIM is also downsampled into a voxel grid at the same resolution. Note that the two voxel grids are in the same coordinate system since the two point clouds have already been registered together.

\[
VG(x, y, z) = \begin{cases} 
1, & \exists (\exists P) s.t. \left(\frac{p_x}{\lambda}, \frac{p_y}{\lambda}, \frac{p_z}{\lambda}\right) = (x, y, z) \\
0, & \text{otherwise}
\end{cases} \quad \text{(Equation 5)}
\]

Based on the difference in occupied states, each voxel can then be labeled as belonging to correctly or incorrectly constructed building components. Each as-planned BIM element, \( E \) is assigned a completion score, \( S \) based on whether the constituent voxels’ occupancy status matches that of the as-built voxel grid (Equation 6). The completion score will be higher for accurately constructed elements and lower for elements that are constructed inaccurately or not yet constructed.

\[
S_E = \frac{\Sigma_{(x,y,z)\in E} VG(x,y,z)}{||E||} \quad \text{(Equation 6)}
\]

3. RESULTS

The proposed algorithm is evaluated on a building construction site dataset spanning a hallway of 100m x 5m x 7m. The dataset contains concrete structures, steel elements, as well as Heating, Ventilation, and Air Conditioning (HVAC) elements. The as-planned BIM model is exported from a professionally-prepared Naviswork file whereas the as-built laser scan data is collected from a FARO laser scanner. Figure 3 shows a 3D visualization of the laser-scanned point cloud and the mesh model from BIM. The two datasets are initially misaligned because the data are collected in different coordinate systems. After applying the column-based scan registration (Steps 2.1 – 2.3), the laser-scanned point cloud is transformed to the same coordinate system as the BIM model. As can be observed in Figure 4, the columns in the point cloud and the mesh model are now aligned properly.
Figure 3. Overlay of laser-scanned point cloud and the mesh model from BIM before registration. The detected column locations are shown in Figure 1.

Figure 4. Overlay of laser-scanned point cloud and the mesh model from BIM after registration. The detected column locations are shown in Figure 2.

Next, the point-to-point deviation method was applied for ductwork and steel structures respectively as shown in in Figures 5 and 6. Each voxel in both the point cloud data and BIM data was labeled as either occupied or unoccupied. Next, each as-planned BIM element is assigned a completion score based on whether the constituent voxels’ occupancy status matches that of the as-built voxel grid and color-coded based on the completion score. The following color-coding scheme is used: (i) green represents accurately constructed elements, (ii) orange-yellow represents elements with minor inconsistencies, and (iii) red represents elements that are not constructed or constructed in the wrong location. This color-coding scheme is selected so that the regions with low and high deviations from the as-built state may be easily visualized.
4. DISCUSSION

Evaluation of the proposed deviation detection method is divided into two parts: (i) quantitative evaluation of the column registration step and (ii) qualitative evaluation of the point-to-point deviation detection step. First, the column-based registration step was evaluated with respect to the rotation and translation error. The ground truth translation and rotation were derived manually and used to verify the accuracy of the estimated translation and rotation. Ten different initial configurations of the laser-scanned point cloud were set randomly, and the same registration method was used to align them with the BIM model. Several values for hyperparameters, such as the height threshold for columns and RANSAC algorithm threshold, were tested and the best results were reported. Across the ten different initial configurations, the achieved rotation error is 0.068 degrees ± 0.050 whereas the translation error is 0.15m ± 0.16. The rotation error achieved is very low since the columns are usually laid out in a linear fashion, and an accurate alignment can be achieved by matching all the columns in a line. On the other hand, the translation error achieved is higher because the column centroid estimation process may be biased by clutter and noise in the point cloud data. Overall, the computation time required for the column detection and registration step is 2.9s per 100,000 points.

The point-to-point deviation detection step also produced reasonable results in the examined dataset. Ductwork that was constructed with a horizontal deviation of around 0.2m as measured manually was correctly flagged as yellow in the results (Figure 5). On the other hand, elements that were correctly constructed were labeled in green (Figures 5 and 6). However, some steel beams and part of the steel columns that were underground were labeled in red, incorrectly signifying that they were wrongly-built. This is because those elements were occluded in the point cloud and resulted in unoccupied voxels in the comparison process. For the point-to-point deviation detection step, the computation time required is 35s per 100,000 points.

The proposed method is advantageous in that the point-to-point comparison step does not depend on object type, such that any building element including ductwork, steel structures, can be examined using the same algorithm. This can help to avoid errors caused by false positives or false negatives in object detection. In addition, the visual highlighting of interest areas allows a human user to quickly identify regions in the jobsite that require attention and apply the necessary corrective action. On the other hand, the limitation of the proposed method is that it cannot quantitatively measure the actual deviation of an as-built object. For example, a positional error that is beyond tolerance by 0.5m will be similarly flagged as one that is beyond tolerance by 1.0m. In addition, the method is not
able to distinguish between unbuilt elements and elements built in the wrong location. This is because both cases will lead to unoccupied voxels in the location where the element is supposed to be built. However, the method is still able to function as an effective site management tool by verifying the correctness of non-deviated and slightly-deviated elements.

5. CONCLUSIONS

This research proposes an automated jobsite inspection technique for identifying deviations between the as-planned and as-built state of building elements. The proposed method utilizes a column-based registration procedure coupled with a point-to-point comparison method for automated scan-vs-BIM deviation detection. Experiments were carried out using laser-scanned point clouds of an indoor hallway to validate the proposed approach. Results show that the proposed column-based registration method achieved a translation error rate of 0.15 meters and a rotation error rate of 0.068 degrees. The computation time required is 3 seconds for the column-based registration step and 70 seconds for the deviation detection step. This research has the potential to reduce the labor costs associated with manual inspection and expedite the construction progress checking procedure. This will, in turn, improve the productivity by creating an effective feedback loop for the construction workforce to identify deviations and correct errors. For future work, more construction site data will be collected to further verify the effectiveness of the proposed approach. In addition, feature point matching and plane matching methods will be used to improve the accuracy of the initial registration step.

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REFERENCES


