DEVELOPMENT OF AN AUTOMATED 3D/4D AS-BUILT MODEL GENERATION SYSTEM FOR CONSTRUCTION PROGRESS MONITORING AND QUALITY CONTROL

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Abstract: Automating the progress monitoring and control process is of great interest to industry practitioners to help improve the limitations associated with the current manual data collection and analysis practices. Two remote sensing technologies, namely, Light Detection and Ranging (LiDAR) and digital camera, are widely used to acquire 3D point clouds as a means of measuring the “scope of the work performed” of structural elements. However, to assign the collected 3D point clouds to their corresponding structural element, current object-based recognition models use the as-planned 4D model, which may not be reliable in cases where the locations of the as-built structure differ from those of the planned, and/or the planned 4D model is not available with sufficient detail. Here, a novel method is proposed to eliminate the dependency on the as-planned data by automatically generating the 3D/4D as-built model through a robust Principal Component Analysis-based (PCA) segmentation algorithm. The proposed system is also independent of the technology used to capture the 3D point clouds. To evaluate the reliability of the proposed automated as-built model generation procedure, two sets of LiDAR data from the "Mechanics of Materials" laboratory and the "Graduate Student Hall of Residence" construction site at the University of Calgary were collected. A novel method of automated registration of the as-built model to the planned model coordinate system is also proposed through which the compliance of the planned vs. actual dimensions of corresponding structural elements are examined. The results of the two experiments demonstrate the applicability of the proposed methods for the automatic generation of the 3D/4D as-built model and the dimension compliance control of structural elements.

1 INTRODUCTION

Project monitoring and control are vital to facilitate decision makers identify deviations between the planned vs. as-built states of the project and take timely measures where required (Maalek and Sadeghpour, 2012). Monitoring is the process of collecting onsite data as a means of measuring the Project Performance Indicators (PPI). Traditionally, onsite data are collected manually, a time consuming, error-prone and labor intensive task particularly on large scale projects (Golparvar-Fard et al. 2009a). In practice, to justify the time and cost associated with such manual approaches, a limited amount (and/or frequency) of onsite data are collected, which diminishes the ability of the project manager to identify the causes of delays and cost overruns on time. In addition, most onsite data collection processes are anecdotal without a proper monitoring plan/strategy (Golparvar-Fard et al. 2011), which influences the time, cost and reliability of the collected PPIs.
Project control involves the processing of the accumulated data for the determination of the performance of the current state of the project. Therefore, the reliability of the determination of the performance of the project is highly dependent on the strategy as well as the accuracy of the collected data during the monitoring process (Saadat and Cretin, 2002). Currently, site supervisory personnel spend 30-50% of their time on manually monitoring and controlling onsite data (McCullouch, 1997, Golparvar-Fard et al. 2009). If this time is reduced by means of a novel approach to onsite data collection and analysis, more time can be allocated to improving vital construction related concerns such as safety (Maalek & Sadeghpour, 2011), and workforce productivity and communications (Choy and Ruwanpura, 2007). Therefore, automating the monitoring and control process is proposed in recent years to help overcome the aforementioned limitations of current manual practices.

2 LITERATURE REVIEW

The percentage of completion of an activity is suggested as the Key Performance Indicator (KPI) capable of providing progress information in activity-level (Maalek et al. 2014). In order to automatically extract this metric, the scope of the work performed for each activity is required to be identified by means of a remote sensing technology. Currently, two remote sensing technologies, namely, digital camera and LiDAR, are widely used to generate 3D coordinates of the surrounding surfaces. The overview of the previous research related to the application of these two technologies for progress monitoring of construction activities are presented in the following.

2.1 Digital Camera

In practice, photographs are commonly taken to record the progress of specific activities and/or to help minimize disputes/claims (Golparvar-Fard et al. 2009a). These images are stored without proper documentation and indexing (Brilakis et al. 2006). In addition, the KPIs are manually extracted from the large number of unordered/randomized images, constituting a costly, lengthy and challenging procedure. Current research aims at improving these aspects by means of automating the extraction of meaningful information from the accumulated images. These research studies can be subcategorized into two groups, namely, those using a single pre-calibrated fixed-location camera, and those using multiple cameras to determine the 3D coordinates of the surrounding surfaces.

2.1.1 Single fixed-location camera

Using a single camera at fixed locations, it is not possible to determine the 3D coordinates of the structural elements (Rougier and Meunier 2010); however, some researchers have innovatively used time-lapsed images to determine the completion and production rate of certain construction activities. Lukins and Trucco (2007), Zhang et al. (2009) Ibrahim et al. (2009) aimed at determining the completion of certain activities on site by detecting the changes between consecutive images. Golparvar-Fard et al. (2009a) aimed at visually identifying the deviations between the plan and the actual states of the construction work by means of color-coding the identified differentiations. Ranaweera et al. (2013) developed a system to automatically determine the productivity of tunnel construction by identifying the number of liners lowered into a tunnel during a shift.

2.1.2 Multiple cameras

As mentioned in the previous section, it is not possible to quantify the “scope of the work performed” (i.e. the progress) of construction activities using a single camera. In addition, since construction sites are dynamic environments with many moving objects, the presence of newly added obstacles may block the Line-Of-Sight (LOS) of the camera. Therefore, additional cameras are required to correctly determine the progress of construction activities. At least two camera exposures taken from different locations are required to estimate the 3D coordinates of a point relative to the image coordinate system using collinearity equations and triangulation (Kraus, 1993). In order to determine the position and orientation of each exposure station, at least three (3) tie-points (point correspondences) are required per image. Recent research studies aim at automatically matching similar features (tie-points) from unordered construction site photographs to generate the 3D coordinates of the surrounding surfaces (point clods).
Golparvar-Fard et al. (2009b, 2011a, 2011b, and 2015) developed an automated progress monitoring system, called, D4AR, which uses the accumulated unorganized photographs to determine the 3D coordinates of structural elements on site. The system uses a dense pixel to pixel matching algorithm to link the similar features between every two image to create a 3D point cloud of the site at the time the monitoring is performed. The system then estimates the translation and rotation of each of the camera exposures with an arbitrarily defined scale via a bundle adjustment. The scale of the measurement is then identified by manually registering some corresponding key points from the planned to the as-built space. At least three point correspondences are required to solve for the seven parameters (including scale; Horn, 1987). It is to emphasize that the manual registration is mandatory since the true 3D coordinates of the point clouds can only be estimated if the scale is defined with respect to the true space. However, the method assumes that the 3D coordinates of the selected key points remain unchanged between the as-built and the as-planned models. In other words, the potential errors in construction are neglected. Therefore, it is likely that the expected accuracy of the generated 3D coordinates drops since construction errors may cause differences between the as-planned and the as-built structure, which consequently affects the scale of the measured point clouds. In order to overcome this challenge, the correctly-scaled coordinates of the key points should ideally be measured by means of an external measurement system (such as a reflector-less total station or a scale bar), which increases the time and cost of data collection as well as possibility of interruption with construction activities. In (Golparvar-fard et al, 2011a, 2011b and 2015), the constructed point clouds from the D4AR system, proposed above, are assigned to their corresponding structural elements by superimposing the as-planned 4D BIM model to the constructed point clouds.

As indicated above, at least two camera exposures are required to estimate the 3D coordinates of a point. Considering the limited Field of View (FOV) of a camera, a large number of manual photographs must be captured in order to cover every structural element on the site at least twice, which increases the time and cost of onsite data collection and analysis (Maalek et al. 2014). In addition, finding point-to-point correspondences between every image pair requires additional processing. In Golparvar-fard et al. (2011a), the processing of 288 images, constructing only 62,000 points, is shown to take approximately 7 hours. Furthermore, the quality of the images taken by a camera is a function of the lighting conditions and thus the accuracy of the generated point cloud can be highly affected by the lighting conditions (Golparvar-fard et al. 2011a). To summarize, the large number of images required due to limited FOV, the additional processing time due to the correspondence problem between the accumulated images and the need for adequate illumination (Dario et al. 2013) has led researchers to use LiDAR to help overcome the aforementioned limitations of implementing cameras on construction sites.

2.2 LiDAR

LiDAR is a remote sensing technology used to collect 3D coordinates of the surrounding surfaces in LOS using only a single scan-station without additional processing (i.e. directly). In addition, LiDAR is more likely to achieve more accurate data compared to those provided by photogrammetry (Golparvar-Fard et al. 2011b and Bhatla et al. 2012). Therefore, the feasibility of preparation of as-built 3D/4D models using LiDAR technology has been of great interest to researchers in recent years.

In the work of (Bosché, 2010, Bosché et al. 2009, 2015, and Turkan et al. 2013), the as-planned 4D CAD model is used to assign the accumulated point clouds to their corresponding structural elements. In their approach, first, the collected point clouds are manually registered to the planned model coordinate system. For each registered scan-station, the point clouds corresponding to the planned model are then generated by considering the potential random errors associated with the LiDAR equipment. If the distance between the two points is smaller than a threshold, the two points are equivalent. For the corresponding points, the Iterative Closest Point (ICP) registration is used to improve the results of the manual registration. In (Turkan et al. 2013), an earned value analysis on the data captured and processed in (Bosché, 2010) was performed. The point clouds were assigned to their corresponding structural elements; however, the “scope of the work performed” for each object was determined manually, which is a time consuming process, especially for in large scale construction projects. In (Bosché et al. 2015), the same procedure presented above was used to first generate the 3D as-planned point clouds on a piping project. A 3D Hough transform was then performed on both the as-planned and
as-built point clouds to determine the circular cross sections. These cross sections were then matched to identify the dimension compliance, location and the completion of the pipes. Zhang and Arditi (2013) also used the as-planned model in order to determine the completion of an object by counting the number of point clouds inside two predetermined boundaries, representing the tolerance region, of the object. Kim et al. (2013) also used the as-planned 4D Building Information Model (BIM) in order to report the progress of construction activities. In their approach the use of connectivity between components as well as sequence of activities were suggested in order to improve the classification results and to deal with misclassifications caused by missing data.

2.3 Some Limitations of Current State of Research

Current object-based recognition models use the planned 4D model as a-priori knowledge to assign the collected 3D point clouds to a structural element (Golparvar-Fard et al. 2009a, 2011a, 2012, 2015 and Bosché et al. 2009, 2015; Bosché, 2010; and Zhang and Arditi 2013), which may not be reliable in cases where the locations of the as-built structure differ from those of the planned (Shahi et al. 2013) or the Issue for Construction (IFC) plan with sufficient detail is not readily available. In other words, the assumption that there are no significant deviations between the as-built and the as-planned states of a project is contradictory to the nature of monitoring and control. In order to reduce this dependency on the details of the planned model, here, it is proposed to summarize the information carried by the accumulated point clouds (regardless of the method the point clouds are generated) into meaningful information that is comparable to the details presented in the planned model (not vice versa). The procedure is explained in more detail in the following sections.

3 OBJECTIVE AND METHODOLOGY

As mentioned previously, the goal of this research is to automatically summarize the accumulated point clouds into vertices that represent the boundaries of the structural elements, which can be used to determine the scope of the work performed. In other words, a novel method is proposed to automatically generate the 3D as-built model of structural elements. For this matter, the geometric primitives (only the 3D coordinates) are used to determine structural vertices from the collected point clouds. The procedure is as depicted in Figure 1. Each element of Figure 1 is explained in more detail in the following sections.

3.1 Point Cloud Classification

Point cloud classification is the process of labeling points with similar physical attributes into predefined classes. Since the most generic building elements as well as most man-made objects (Nunnally, 2010; Vosselman et al. 2004) are constructed from the intersection of planar surfaces, the classification of point clouds into planar surfaces is the major focus of this study. There are two methods commonly used to classify point clouds into planar surfaces, namely, the Hough transform and Principal Component Analysis (PCA). However, the use of Hough transformation for planar classification is computationally expensive and the results of the classification are highly affected by the presence of outlying data (Lari, 2014). Therefore, PCA-based classification is used in this study.

PCA is used to summarize the variation of a multivariate data set into independent (orthogonal) axes. These axes are regarded as the principal components. The magnitudes of these axes represent the variation of the data set in the direction of the axis. This is accomplished by decomposing the covariance matrix of the data set into its eigenvalues and eigenvectors. In case of a 3-dimensional data set such as a point cloud, three orthogonal axes can be determined, which represent the maximum variations of the data set. For noise-free, coplanar points, the data has no variation in the direction of the surface normal. In other words, the eigenvalue corresponding to the direction of the surface normal is equal to zero. For
this matter, many researchers have used PCA for the classification of planar surfaces (Lari, 2014). First, a neighborhood is defined around each point cloud. The PCA is performed on the pre-defined neighborhood of each point. If the pattern of the neighborhood of the desired point forms a planar surface (i.e. smallest eigenvalue is close to zero), the point is classified as a plane. This can be further illustrated in Figure 2.

![Diagram of classification process](image)

**Figure 2:** Classification of accumulated point clouds into planar surfaces

The classification of point clouds into planar surfaces is trivial in ideal, controlled conditions with no data contamination. However, in a construction, due to the data artifacts caused by moving objects, occlusions and dust, outliers are present in the data. The classical method of PCA, which uses the classical estimate of the covariance matrix, is highly sensitive to outliers (Hubert et al. 2012). Therefore, in order to help reduce the effects of outliers on the underlying pattern of the data, the Deterministic Minimum Covariance Determinant (DetMCD) estimate, proposed by Hubert et al. (2012), is used here to robustly estimate the covariance matrix of the data.

### 3.2 Point Cloud Segmentation

Segmentation is the process of grouping the points of a certain class that possess similar attributes. To segment the classified point clouds with similar characteristics, two methods are generally used namely, region growing and clustering. Region growing methods are widely used due to their computational efficiency; however, they are not considered as robust methods since the results of the segmentation is dependent on the selected initial seed point (Wang and Shan, 2009; Lari, 2014). Therefore, clustering methods are used in this research to provide more robust segmentation results.

Generally, there are four main clustering algorithms presented in (Jain and Dubes, 1988). In the research carried out by Milligan and Isaac (1980), the complete linkage method was shown to be more efficient than the others in identifying compact clusters. In this research, an iterative planar clustering method is proposed, using a novel robust complete linkage method, in order to robustly determine planar clusters from unorganized point clouds.

#### 3.2.1 Boundary Detection to Ensure Surface Continuity

Using the proposed clustering algorithm, it is possible to clustered coplanar point which are spatially discontinuous. In order to enforce surface continuity within each cluster, the boundary points of each cluster is determined using the modified “convex hull” algorithm proposed by Sampath and Shan (2007). This approach ensures that the disconnected surfaces are segmented into different clusters.

#### 3.2.2 Robust Plane Fitting

After the boundary detection, each cluster contains coplanar point clouds from continuous surfaces. All the information carried by the points within a planar cluster can hence be summarized into a normal vector and a point, which represent the plane parameters of the cluster. The robust PCA using the Deterministic MCD is used to robustly estimate the aforementioned plane parameters. The robust PCA ensures that local surface roughness due to construction errors and/or outlying data do not affect the result of the plane fitting.

### 3.3 Surface Intersection

As indicated in Section 3.1, most common structural elements are constructed by the intersection of planar surfaces. The method proposed above can theoretically determine the planar facets of structural
elements on a construction site. Therefore, to determine the vertices of these types of structural elements, the closest planes are required to be intersected. For this matter, the planes whose boundaries are closer than the pre-defined threshold are first identified. The line of intersection of every pair of adjacent planes is then calculated. The neighboring points on the two planar clusters are then projected on the intersecting line. The upper bound and the lower bound of the line will be determined based on the position of the projected points. For the two end points of every identified line-segment, the closest end points of the remaining line-segments (within a threshold) are determined. The closest lines are then intersected in order to refine the end points of the line segments. The resulting end points are the vertices of the object of interest.

4 EXPERIMENTS

In Section 3, a fully automated method was proposed to robustly determine the boundaries of structural elements that are constructed from the intersection of planar surfaces. In this section, two experiments designed to assess the effectiveness of the proposed method for automatic 3D as-built model generation are described.

4.1 Monitoring Technology

The benefits of LiDAR to photogrammetry in generating 3D point clouds of the surrounding surfaces were outlined in Section 2.1.2. In addition, the resolution achieved by photogrammetry may not be sufficient to accurately classify and segment the acquired point clouds”. Therefore, LiDAR is the preferred alternative to generate 3D coordinates of the surrounding surfaces (Maalek et al. 2014). The Leica HDS6100 is used in this study to capture the required data. This device has the ability to collect up to 508,000 points per second (Leica, 2009).

4.2 Experiment 1: Mechanics of Materials Laboratory

Using the Leica HDS6100, one set of LiDAR data, consisting of three scan-stations, was collected from the Mechanics of Materials laboratory at the University of Calgary (Figure 3). As illustrated in Figure 3a, the laboratory consists of many obstacles and metallic tables, which may increase the possibility of occlusions as well as loss of accuracy due to multipath reflection. Therefore, it may be considered as a fair representation of an actual indoor construction site. Approximately 30 million 3D points of the interior surfaces were recorded from the three scan-stations. The total data collection time was less than 15 minutes for all scan stations. As illustrated in Figure 3b, the lab consists of 26 different walls. The elevation of the ceiling relative to the floor is 2.7 m. The planned model suggests that the roof, floor and the surrounding walls are planar surfaces. The plot of the plan of the site represents a concave polygon.

![Figure 3: a) "Mechanics of Material" laboratory; b) plan view of the laboratory](image_url)
4.2.1 Floor and Flat Slab Ceiling Extraction

Here, a method is proposed to identify and extract the points on the floor and the flat slab ceilings without performing a robust PCA. This is especially beneficial to help reduce the calculation time of the segmentation process. It can be demonstrated that the histogram of point elevation for any room similar to the lab used in this study has the form shown in Figure 4a. As illustrated, the histogram of elevation consists of two major peaks, which represent the points of the floor and the ceiling. To determine the location of these two modes, the Median-shift algorithm proposed by Shapira et al. (2009) was used. The two modes are regarded as points Pf and Pc in Figure 4a. In order to robustly identify the points on the ceiling and the floor using the identified modes (peaks), first all the points in \( \pm r_f (r_c) \) from the mode Pf (Pc) are identified. \( r_f (r_c) \) is the difference of the minimum (maximum) elevation of the data set from the elevation of first (last) meaningful mode Pf (Pc). The Deterministic MCD algorithm was then applied on these specified points in order to identify the subset that complies with the majority of the dataset. The identified points with the least variation are then regarded as the points on the floor and ceiling.

![Figure 4: a) Expected distribution of the elevation of the point cloud; b) histogram of elevation of the actual point cloud.](image)

The histogram of elevation is as shown in Figure 4b, which complies with the hypothesis presented in Figure 4a. The objective is to determine the points of the floor and the ceiling, enclosed by the red ovals of Figure 4b. The results of the extracted points using the robust method described above are presented in Table 1. As illustrated, no Type II errors were detected during the extraction of the feature extraction, which indicates the robustness of the proposed method. In addition, the extracted points accounted for approximately half of the total accumulated point clouds, which suggest a significant reduction in the time of data classification and segmentation.

<table>
<thead>
<tr>
<th>Surface</th>
<th>( t_n )</th>
<th>( t_p )</th>
<th>( f_n )</th>
<th>( f_p )</th>
<th>Precision (%)</th>
<th>Recall (%)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Floor</td>
<td>252392</td>
<td>3897455</td>
<td>0</td>
<td>361429</td>
<td>91.5</td>
<td>100.0</td>
<td>92.0</td>
</tr>
<tr>
<td>Ceiling</td>
<td>1917447</td>
<td>11633097</td>
<td>0</td>
<td>959045</td>
<td>92.4</td>
<td>100.0</td>
<td>93.4</td>
</tr>
</tbody>
</table>

4.2.2 Segmentation and As-built Model

Using the methods presented in Section 3, the remaining point cloud was segmented with 94.7% accuracy. The results of the segmentation are as shown in Figure 5a, where the different colours represent different clusters. The purple colour represents the boundaries of the segments. Figure 5b shows the as-built 3D model of the site after the nearest planar clusters are intersected.

4.2.3 Automatic Registration

Here, a novel method is proposed to automatically register the generated as-built model to the planned model coordinate system. Figure 6 shows the plan view of the 3D as-built CAD model. In order to automatically determine the point to point correspondence between the as-built and the planned, two metrics are defined for every vertex (Figure 6a). The first is the angle between the vector that enters and
exits the vertex \((\theta)\). The second is the average of the magnitude of the vector entering \((V_1)\) and exiting \((V_2)\) the vertex. The point correspondences are then determined based on the similarity of the two metrics using a one-step complete linkage clustering method. The method proposed by Horn (1987) is then used to perform a rigid body transformation and completed the registration process. The results indicated a 9.4 cm Mean-Radial Spherical Error (MRSE), which represents the potential discrepancies between the planned model and the captured data. The horizontal and the vertical dimensions of the walls were 7.5 cm and 2.4 cm different respectively.

Figure 5: a) Segmentation results (obstacles are removed for clarity); b) as-built 3D CAD model

4.3 Experiment 2: Graduate Student Hall of Residence

The objective of this experiment is to generate the as-built model of the elevator shaft for the Graduate Student Hall of Residence construction site at the University of Calgary. The elevator shaft is a concrete structure consisting of four perpendicular planar surfaces. The as-built dimensions of the shaft were of particular interest to the contractor since these dimensions are required to comply with the specification of the ordered elevator. A ±2 cm tolerance from the planned dimensions was acceptable for the contractor. The as-built model of the elevator shaft was generated using method proposed in Section 3 as illustrated in Figure 6b &c. The results of this experiment indicated a Distance Root Mean Squared of 1.8 cm, which complies with the standards presented in the project plan and the acceptable tolerance region.

Figure 6: Mechanics of Materials Laboratory: a) Plan view of the as-built model prior to registration; Graduate Student Hall of Residence: b) Collected LiDAR point clouds from the elevator shaft; c) automatically generated as-built 3D CAD model

5 CONCLUSION

In this study, a novel method for the automatic generation of the 3D/4D as-built model of planar structural elements was proposed without using the as-planned data. As-built models are of particular importance to the owner for renovation, maintenance as well as demolition of the existing structure. The proposed
system is a stand-alone method that can be used to assess the progress of construction activities even at times when the planned model is not available. The planned model is however, required to assess the deviations between the planned and the actual states of the project. This approach uses a novel robust PCA to first classify coplanar point clouds. The classified points are then segmented using the complete linkage clustering method. The boundary points of each cluster are determined to break discontinuous surfaces into smaller segments. The planar surfaces are then intersected to determine the vertices of the objects of desire. A novel method is also proposed to robustly extract the floor and flat slab ceilings without the need for the aforementioned approach, which can help reduce the calculation time significantly. A new method of automated registration and point to point correspondence search is also proposed. The two experiments show the effectiveness of the proposed system in automatically generating the 3D as-built model in both a highly occluded laboratory and an actual construction site environment.

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