Automatic As-built BIM Creation of Precast Concrete Bridge Deck Panels Using Laser Scan Data

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Abstract

Precast concrete bridge deck panels are commonly used for bridge constructions because they enable faster construction and have less impact on traffic flow. The quality of connections between adjacent precast elements must be ensured to guarantee the overall structural integrity of precast systems. Therefore, the dimensional quality of precast concrete panels should be inspected before they are shipped to construction sites for installation. However, current quality inspection of precast concrete elements mainly relies on manual inspection. Furthermore, the as-built dimensions of precast elements are usually stored in paper sheets or Excel spreadsheets, making it difficult to visualize and manage the as-built dimensions. This study develops a technique to automatically estimate the dimensions of precast concrete bridge deck panels and create as-built building information modeling (BIM) models to store the real dimensions of the panels. First, the proposed technique conducts scan planning to find the optimal scanner locations for scan data acquisition. Then, the scan data of the target panel are acquired and pre-processed to remove noise

data and to register multiple scans in a global coordinate system. From the registered scan data, the as-built geometries of the target panel are estimated. In the last step, an as-built BIM model is created based on the previously estimated geometries. The proposed technique is validated on a lab-scale specimen and a full-scale precast concrete bridge deck panel. Experimental results show that the proposed technique can accurately and efficiently estimate the dimensions of full-scale precast concrete bridge deck panels with an accuracy of 3 mm and automatically create as-built BIM models of the panels.

Introduction

Precast concrete bridge decks have been adopted in the construction of bridges since 1960s (Alhassan 2011). Compared to cast-in-place (CIP) construction, precast bridge decks offer the following three advantages (Hieber et al. 2005). First, the quality of precast bridge decks is superior because they are produced in a controlled plant environment, which has consistent casting operations and curing processes. Second, precast bridge decks can reduce construction time by 50% to 75%, thereby reducing the impact on the traffic flow and the safety hazards to workers. Third, although precast bridge decks have higher initial costs, the life-cycle costs considering road users and traffic maintenance costs are significantly below those of CIP decks.

A typical precast bridge deck consists of a series of precast bridge deck panels. The short sides of bridge deck panels are parallel with the traffic flow, also known as the longitudinal side surfaces. On the other hand, the long sides of bridge deck panels are known as transverse side surfaces. Fig. 1 shows a typical precast concrete bridge deck panel with shear pockets, shear keys, and flat ducts, which are all needed to connect the panel with a girder or an adjacent panel. Shear pockets are distributed on the top surface of the panel, serving as panel-to-girder connections. Shear connectors (e.g., studs) on a girder are inserted into the corresponding shear pockets, and grout is filled in the shear pockets for coupled behavior of the panel and girder. The stud-to-shear-pocket connections prevent both horizontal and vertical movements between the panel and the girder. Shear keys are introduced on the transverse side surfaces of panels to prevent relative movements between two adjacent panels and to transfer vertical loading from one panel to the other. The gaps between two consecutive panels are also filled with grout for continuous behavior of the panels. Flat ducts are also introduced on the transverse side surfaces. Post-tension cables pass through the flat ducts, and the connected panels are subjected to compression when tension is applied to the cables via hydraulic jacking (Alhassan 2011).

To guarantee proper connections between adjacent precast elements, the dimensional quality of individual precast concrete panels, especially the structural features, must be inspected before the panels are transported to construction sites for installation. The Precast/Prestressed Concrete Institute (PCI) has specified a quality control check list for precast concrete bridge units, as shown in Table 1 (Gutt et al. 2000). The tolerance values used in the quality control check list mostly vary from 6 mm to 13 mm.

Current quality inspection of precast concrete panels mainly relies on manual inspection using traditional measurement tools. Such manual inspection was proven to be subjective and unreliable. According to Phares et al. (2004), 32% of the bridge component condition ratings performed by manual inspection varied for at least two rating points (rating scale: 0-9). In additional, manual inspection is time-consuming, especially for large size structures. For example, according to Wang et al. (2017), it took around 40 minutes to manually inspect the positions of 88 rebars installed on a 12 m long reinforced precast concrete panel, resulting in increased labor cost. Although electronic survey devices such as total stations and laser range finders (Suo et al. 2014; Koo et al. 2013) can provide faster and more accurate dimension measurements, it is still time-consuming to acquire high-fidelity surveying data for large-scale precast concrete panels. Furthermore, current practice is to manually store the as-built dimensions of inspected panels in paper sheets or Excel spreadsheets, making it difficult to visualize and manage the actual dimensions of the panels.

In the recent decades, 3D laser scanning and building information modeling (BIM) are adopted in the construction industry. 3D laser scanning can acquire 3D range measurement data with high accuracy and a high speed, thereby gaining popularity in various applications including dimension estimation (Tang et al. 2009; Riveiro et al. 2013; Bosché 2010; Kim et al. 2014a; Wang et al. 2016a; Wang et al. 2016c; Kim et al. 2016; Wang et al. 2017), surface quality evaluation (Monserrat and Crosetto 2008; Tang et al. 2010a; Bosché and Guenet 2014; Wang et al. 2016b; Kim et al. 2014b), and construction progress tracking (El-Omari and Moselhi 2008; Turkan et al. 2012; Kim et al. 2013). On the other hand, BIM, as a technology for the storage, visualization and management of facility information, has been used throughout the lifecycle of buildings and civil infrastructures. Research efforts have been also made on automatic creation of as-built BIM from 3D laser scan data of facilities (Brilakis et al. 2010; Pu and Vosselman 2009; Tang et al. 2010b; Xiong et al. 2013; Arayici 2007).

The authors' research group has previously developed techniques for dimension estimations of precast concrete panels using laser scan data (Kim et al. 2014a; Wang et al. 2016a; Kim et al. 2016). However, the previous techniques have the following limitations. First, only one surface of the target panel is scanned from a single scanner location for dimension estimation. Cases with multiple surfaces and multiple scanner locations are not taken into consideration. Second, a prior as-designed BIM of the panel is required to extract the as-built dimensions of structural features from laser scan data. This dependency on the prior as-designed BIM limits the applicability of the previous techniques when the as-designed BIM is not available. Third, the as-built dimensions of the panel are not automatically transferred to BIM, making it difficult to visualize and manage the actual dimensions of the panel.

To overcome the above-mentioned limitations, this study develops an automatic as-built BIM creation technique for precast concrete bridge deck panels. The developed technique aims to estimate the as-built dimensions of bridge deck panels and to automatically create an as-built BIM from the estimated dimensions. The proposed technique first conducts scan planning to determine the optimal scanner locations that can acquire scan data with the minimum number of scanner locations, while fulfilling certain criteria. Then, the target panel is scanned from the selected optimal scanner locations, and the obtained scan data are pre-processed for noise removal and registration of multiple scans. Next, the as-built geometries of the target panel are extracted from the registered laser scan data. Particularly, the proposed technique can automatically extract certain structural features based only on the as-designed dimensions of the corresponding features, but without the as-designed BIM model of the entire structure. Finally, an as-built BIM model is automatically created based on the estimated dimensions of the target panel. The uniqueness of the proposed technique includes (1) the development of a scan planning algorithm that enables automatic registration of scans, (2) the development of an automatic structural feature extraction algorithm without corresponding as-designed BIM, and (3) the development of an automatic algorithm for creating an as-built BIM model of a precast concrete panel from the scan data.

Literature Review

This section provides a brief literature review related to scan planning, laser scanning based quality assessment, and as-built BIM creation from laser scan data.

Scan planning

Scan planning aims to prepare a scanning strategy in advance so that the acquired scan data can achieve certain requirements and the data acquisition time can be minimized. Several studies have been reported on the scan planning of buildings and civil infrastructure. Argüelles-Fraga et al. (2013) presented an algorithm to determine scanning parameters that satisfy prescribed accuracy while minimizing the scanning time. The focus was scanning of circular cross-section tunnels. Biswas et al. (2015) automatically generated laser scanning strategies based on a 3D BIM model of the target facility and the characteristics and specifications of the laser scanner. They also took into consideration the occlusions among facility components. Zhang et al. (2016) proposed a rapid scan planning method using the "divide-and-conquer" strategy. The strategy first clustered target points that need to be scanned and then found the scanner locations for each cluster individually.

However, the existing literature on scan planning fails to consider enough overlap between scan data, thereby failing to achieve fully automatic registration of multiple scans. In most of the literature, scan registration is still performed by manually picking common points of two scans, which is time-consuming when dealing with a large number of scan datasets.

Laser scanning based quality assessment

A couple of studies have applied 3D laser scanning to the dimensional quality assessment of construction components. For example, Alba et al. (2006) monitored the deformations of a large concrete dam by comparing laser scan data obtained at different times. Bosché (2010) presented a dimensional compliance check approach for automatically calculating the as-built dimensions of steel columns by registering the laser scan data to the 3D CAD models. Kim et al. (2016) performed dimensional quality assurance of full-scale precast concrete panels based on terrestrial laser scanning and BIM. Wang et al. (2016a) proposed a technique which inspected the dimensional quality of the side surfaces of precast concrete panels.

Research efforts have also been reported on assessing surface conditions of structural components using laser scan data. Tang et al. (2010a) proposed an evaluation framework to evaluate the performance of different algorithms and scanners for detecting concrete surface defects. Kim et al. (2014b) proposed a technique to simultaneously localize and quantify spalling defects on concrete surfaces from laser scan data. Bosché and Guenet (2014) presented an approach for automatically applying two different standard flatness control techniques to the laser scan data and assessing the floor flatness based on prescribed tolerances. Wang et al. (2016b) reported techniques to automatically inspect the surface flatness and distortion of precast concrete elements using terrestrial laser scanning.

The major limitation of the aforementioned techniques is that the as-designed BIM is often required to recognize objects from the laser scan data. For example, Wang et al. (2016a) aligned the laser scan data of a precast concrete panel with the as-designed BIM to find the locations of shear keys. Here, the as-built objects are assumed to be located close enough to the as-designed ones after alignment. In reality, the as-designed BIM model may not be available, and, even when the as-designed BIM is available, the discrepancy between the as-built and as-designed objects can be significant especially for large scale components. Furthermore, since the previous quality assessment of precast concrete panels is based only on a single scan, the scan data resolution was limited and the dimension estimation errors could be large (more than 6 mm) (Kim et al. 2016).

As-built BIM creation from laser scan data

Because manual creation of BIM from laser scan data is time-consuming and labor-intensive, researchers have developed techniques to automate the BIM creation process. Here, the main challenges are (1) the registration of multiple scans, (2) geometric modeling, and (3) object recognition.

To generate point cloud data covering all surfaces of a target object, often multiple scans need to be conducted at different locations. Then, the scan data obtained from different scanner locations are transformed into a global coordinate system. The most well known method for point cloud registration is the iterative closest point (ICP) algorithm (Besl and McKay 1992; Chen and Medioni 1991). The ICP algorithm takes one point cloud as the reference and the other point cloud is iteratively transformed to approach the reference by minimizing the distances between them. Many variants of the ICP algorithm are also developed such as the Generalized-ICP algorithm (Segal et al. 2009). However, the ICP algorithm requires a large overlapping area, and the final solution depends on the initial starting point. Additional algorithms for automatic registration based on 3D features have been developed in the computer vision area, such as works by Huber and Hebert (2003) and Makadia et al. (2006). However, the application of these algorithms to the construction industry has been limited due to self-similarities and lack of "3D features" of construction components. Instead, plane-based registration approaches have been proposed specifically for the construction industry, considering that most surfaces of construction components are planar (Bosché 2012). For example, Dold and Brenner (2006) searched for corresponding planar patches in two overlapping scans for the registration of scan data. In many previous studies (Bosché 2010, Bosché 2012, Turkan et al. 2013), a two-step registration approach, which consisted of 1) a coarse registration using geometric features (such as corresponding planes) and 2) a fine registration using the ICP algorithm, is adopted. In this study, considering that surfaces of precast concrete panels are mostly planar as well, the registration approach containing a corresponding-plane-based coarse registration and an ICP-based fine registration is adopted.

Geometric modeling refers to the process of detecting and modeling certain geometric shapes from scan data. The most common shape in the construction industry is a plane. A number of algorithms have been adopted to detect planes, including the random sample consensus (RANSAC) algorithm (Bosché 2012), the Hough transform (Tarsha-Kurdi et al. 2007), and the region-growing algorithm (Xiong et al. 2013). Besides planar surfaces, cylindrical shapes, which can represent pipes, columns and conduits, have also been studied (Bosché et al. 2015). In this study, surfaces of precast concrete panels are mostly planar and the RANSAC algorithm is adopted to extract planes as it has been proven to be efficient and effective for construction components (Bosché 2012, Jung et al. 2014, Martínez et al. 2012).

Object recognition aims to recognize specific construction components (e.g., wall, roof, and column) from the detected geometric shapes. Many approaches for automatic object recognition from 3D point cloud data have been proposed. Johnson et al. (1997) used a spin image to describe the shape of each CAD model and then each point cloud data was recognized by comparing its spin image with the spin images of all CAD models. Huber et al. (2004) proposed a parts-based method for classifying scenes of 3D objects, in which objects were divided into individually recognizable parts. This approach enabled a more flexible class representation and allowed scenes in which the query object was significantly occluded. Xiong et al. (2013) applied a machine learning algorithm such that the algorithm can learn the unique features of different construction components and contextual relationships among them in order to automatically label planar scan data segments. Rusu et al. (2008) used functional reasoning for assigning a dataset to an object class using commonsense knowledge (either hardcoded or acquired through learning) for household environments. Pu and Vosselman (2009) introduced prior knowledge about different building components so that these components can be recognized from laser scan data segments. Valero et al. (2015) combined radio frequency identification (RFID) technology with laser scanning to recognize and model furniture ncluding tables, chairs, and wardrobe-like objects. Although a large volume of literature is available for the recognition of building components or indoor scenes from point cloud data for building components or indoor scenes, few literature has been reported on civil infrastructure components. The geometries of civil infrastructure components are substantially different from those of building components. For example, a single bridge component (e.g., a pier, girder, or deck unit) can be much larger and more complex than a specific building component (e.g., wall, floor, door, etc.), making it difficult to apply the previous research efforts on building components to civil infrastructure components.

Proposed Technique

The proposed automatic as-built BIM creation technique consists of five steps, (1) scan planning, (2) data acquisition and noise removal, (3) scan registration, (4) geometry extraction, and (5) as-built BIM creation. The details of each step are illustrated in the following.

Scan Planning

Scan planning aims to find the optimal scanner locations for scanning the target panel. The optimal scanner locations should minimize the total number of scans while fulfilling the following five performance criteria.

(1) Level of accuracy (LOA), which measures how accurate the laser scan data are. For any specific point on the target, at least one scan should meet the LOA criterion. Although the measurement accuracy of a scan point is decided by many factors including the scanner's measurement model, scanning distance to the object, incident angle of the laser beam, and reflectivity of the surface (Boehler et al. 2003), the dominant factor in this study was the incident angle of laser beams. According to Soudarissanane et al. (2009), the measurement accuracy

decreases as incident angle increases, especially when incident angle is larger than 70°. As for the specific laser scanner model used in this study, the ranging accuracy with scanning distance of less than 25 m and surface reflectivity of higher than 10% is always higher than 1.1 mm (FARO, 2017). The scanning distance was always less than 20 m in this study considering the scale of the precast concrete panels, and the surface reflectivity of concrete panel surfaces was higher than 35%. Therefore, the accuracy was not much affected by the laser scanner model, the scanning distance nor the reflectivity of the concrete surface. Therefore, to fulfill the criterion of LOA, the incident angle α should be kept below a certain threshold value of α_t.

(2) Level of detail (LOD), which measures how detailed the laser scan data are. To satisfy the LOD criterion, the spatial resolution s (i.e., spacing between two adjacent scan points) should be less than a threshold value of s_t. The spatial resolution s is decided by the angular resolution of the laser beams, scanning distance to the object, and incident angle of the laser beam. The relationship between spatial resolution and these parameters is explained in Figure 3. Note that the LOA and LOD criteria for a specific point on the target must be fulfilled by the same scan.

(3) Enabling full registration. In order to facilitate automatic registration of scans in the further step, all the scans must be able to be registered based on common planes between scans. Fig. 2 shows an example, where the target panel has four planes (*P1*, *P2*, *P3*, *P4*) to scan and three scans (*S1*, *S2*, *S3*) from different locations are conducted. In case 1, *S1* covers *P1* and *P2*, *S2* covers *P2* and *P4*, and *S3* covers *P3* and *P4*. Since *S1* and *S2* have a common plane (*P2*), they can be registered based on the common plane. Similarly, *S3* can also be registered with other two scans so that all the three scans are successfully registered. On the other hand, case 2 assumes that *S3* covers only *P3*. In this case, *S3* has no common plane with any other scan so that all the three scans cannot be registered. Note that only the six major planes of a typical cuboid panel are likely to

become common planes for registration. The small-size planes of structural features, such as shear keys, are not considered here.

(4) Scan coverage. Among all candidate scanner locations, a scanner location that can cover a large area of the target panel is preferred. As shown in Fig. 3, When a scanner is placed at a normal distance of d from the target panel to get qualified (fulfilling the LOA and LOD criteria) scan data for point P, the incident angle α and spatial resolution s must fulfill the following equations:

$$\alpha \leq \alpha_t \tag{1}$$

$$s \leq s_t \tag{2}$$

where α and s are obtained as follows:

$$\alpha = \operatorname{atan}\frac{x}{d} \tag{3}$$

$$s = \frac{w}{\cos\alpha} = \frac{\theta\sqrt{d^2 + x^2}}{d/\sqrt{d^2 + x^2}} = \theta(d + \frac{x^2}{d}) \tag{4}$$

where θ is the angular resolution, i.e., the angle difference between two consecutive laser beams . From Equations (1)-(4), for a specific d value, the maximum value of x (the scan coverage) becomes:

$$x_{max} = \min(d\tan\alpha_t\,, \sqrt{d(\frac{s_t}{\theta} - d)}) \tag{5}$$

It means that, when a scanner is placed at a normal distance of d from the target panel, the scan coverage, which meets both the LOA and LOD criteria, becomes a circular area with a radius of x_{max}.

Note that the value of d is bounded between 0 and s_t/θ. Fig. 4 shows the relation between d

and $d \tan \alpha_t$ (straight line) and $\sqrt{d(\frac{s_t}{\theta} - d)}$ (curve). As x_{max} is defined as the minimum between $d \tan \alpha_t$ and $\sqrt{d(\frac{s_t}{\theta} - d)}$), the relation between d and x_{max} is shown as solid lines in Fig. 4. It is shown that x_{max} increases from 0 to a maximum value, denoted as X, and then decreases to 0. As for this scan coverage criterion, only scanner locations that can cover a circular area with the radius of $X/2$ or larger are considered as feasible scanner locations.

(5) Field constraints. When it comes to field applications, the placement of a laser scanner is constrained by factors including physical space available, flatness of the ground, and ambient vibration. For example, it is typically advantageous to place the scanner at a high elevation position so that a large area of the target object can be scanned with minimum number of scans. However, the laser scanner is usually mounted on a tripod and the height of the tripod can only be adjusted within a certain range, which limits the height of feasible scanner locations.

The optimal scanner locations are selected considering the above-mentioned five criteria. First, feasible scanner locations are identified based on the scan coverage and field constraint criteria. Then, the optimal scanner locations are selected among all the feasible scanner locations considering the LOA, LOD, and enabling full registration criteria. Since it takes a long computational time to find the optimal scanner locations by exhaustive search among feasible scanner locations, a greedy algorithm is adopted in this study. The greedy algorithm is an algorithmic paradigm that follows the problem solving heuristic of making the locally optimal choice at each stage (Black 2004).

The greedy algorithm for finding the optimal scanner locations is illustrated in Fig. 5, and explained as follows. (1) The algorithm finds the first scanner location as the one that provides qualified scan data for the largest number of points on the target panel. If multiple candidate scanner locations provide qualified data for the same number of points, the algorithm chooses the one that covers the largest number of planes. (2) The algorithm continues finding the second scanner location that provides the largest number of qualified new scan data points from the area not covered by the first scan, also at least shares one common plane with the previous scans. (3) If all the five criteria are still not fulfilled, the algorithm continues finding the next scanner location until all the criteria are fulfilled.

Data Acquisition and Noise Removal

After the optimal scanner locations are obtained through scan planning, the scan data of the target panel are obtained from the selected scanner locations. The data processing starts with noise removal, which aims to eliminate noise data including background points and mixed pixels while retaining valid points representing the target panel. Here, mixed pixels are a type of noise data which occur when the laser beam is split into two parts and lies on both the target surface and the background surface, respectively. While both reflected signals from two surfaces are received by the scanner, the resulting scan point can be anywhere along the line of the laser beam. A DBSCAN based data classification algorithm developed by Wang et al. (2016a) is adopted in this study for noise removal. Based on the spatial densities of scan points, the algorithm classifies low density points (e.g., mixed pixels) as noise data and the valid points with high density as one cluster. Fig. 6 shows an example, where the valid points are grouped together as one cluster, background points as several clusters in different colors, and mixed pixels as noises. Among all the clusters, the one closest to the laser scanner is chosen and regarded as the valid points representing the target panel. Note that mixed pixels do not always have lower densities than valid points. Therefore, it is possible that some mixed pixels still remain in the dataset while some valid points are removed occasionally.

Scan Registration

Scan registration aims to register multiple scans in a global coordinate system based on the common planes between scans, as illustrated in the following four steps.

(1) Extraction of planes from each scan using the RANSAC algorithm (Fischler and Bolles 1981). RANSAC is an iterative method to estimate parameters of a mathematical model (i.e., plane model in this step) from a set of observed data containing outliers. For example, the top plane of a precast concrete panel shown in Fig. 7(b) is successfully extracted from the scan data in Fig. 7(a) using the RANASC algorithm. When a scan covers more than one surface of the target panel, all these planes are extracted.

(2) Identification of common planes between scans. In the scan planning stage, the following information is already known: (a)Which scans share the common plane and (b) Which part of the precast concrete panel (e.g., top plane, long side plane, or short side plane) is the common plane. Therefore, in this step, we only need to identify which plane is the common plane if one scan covers more than one plane. For a typical cuboid panel, one scan can at most cover three different planes (a top plane, a long side plane, and a short side plane), which usually have substantially different sizes. Thus, if one scan covers more than one plane, the common plane can be identified based on the sizes of planes.

(3) Coarse registration of two scans based on their common plane. First, the centroid of the common plane is computed from each scan by averaging the coordinates of all data points within the common plane. Second, three principal axes of the common plane are computed by performing principal component analysis on the scan data points within the common plan. Third, by aligning the centroid and principal axes of the common plane from two scans, the two scans are coarsely registered. For example, two different scans shown in Fig. 7(a) and Fig. 7(c) are registered based

on their common plane (i.e., the top plane), and the registered scan data are shown in Fig. 7(d).

(4) Fine registration of two scans with a common plane using the iterative closest point (ICP) algorithm. As shown in Fig. 7(e), distances between the two scans are further reduced after fine registration, showing a better registration result than coarse registration.

Geometry Extraction

This step extracts the as-built geometries of the target panel, including the extraction of structural features and the extraction of outer boundaries of the panel, as illustrated in the following.

Extraction of Structural Features

Extraction of structural features aims to extract the locations and dimensions of structural features such as shear pockets, shear keys, and flat ducts, from the laser scan data. Various techniques are available for detecting a certain shape from 3D scan data or 2D images such as the RANSAC based shape detection from 3D point cloud (Schnabel et al. 2007) and the template matching approach for 2D images (Gonzalez 1977). In this study, 3D point cloud data are transformed into a 2D image and the template matching approach is adopted to detect certain structural features due to a high computational efficiency in 2D domain analysis.

Template matching is a technique commonly used in digital image processing for finding small parts of an image f which match a template image ω (Gonzalez 1977). At each location (x, y) of image f, a sub-image with the same size as the template image ω is extracted. Then, the normalized cross-correlation coefficient $c(x, y)$ between the sub-image of image f and the template image ω is calculated as:

$$c(x,y) = \frac{\sum_s \sum_t [\omega(s,t) - \bar{\omega}]\left[f(x+s,y+t) - \bar{f}(x+s,y+t)\right]}{\sqrt{\sum_s \sum_t [\omega(s,t) - \bar{\omega}]^2 \sum_s \sum_t \left[f(x+s,y+t) - \bar{f}(x+s,y+t)\right]^2}} \tag{6}$$

where $\bar{\omega}$ is the average value of ω and $\bar{f}(x+s,y+t)$ is the average value of f in the sub-image. After calculating the cross-correlation coefficient values for each location of image f, a cross-correlation coefficient image is generated, as shown in Fig. 8. A higher cross-correlation coefficient value indicates that the corresponding sub-image of image f matches better with the template image ω. Thus, the pixel with the highest cross-correlation coefficient value indicates the most probable location of the template image in image f.

The developed structural feature extraction technique based on template matching is performed in the following five steps.

(1) Generation of an image from scan data. First, the 3D laser scan data from a surface is transformed into a 2D image. The pixel size of the 2D image is equal to the average spatial resolution of the scan data. In Fig. 9, the laser scan data of the top surface of a precast concrete panel is projected onto the least-square fitted plane of the top surface and transformed into a 2D image. Here, the pixel values corresponding to the surface are assigned to one (white color in Fig. 9(b)), and the remaining pixel values corresponding to the shear pockets are assigned to zero (black color). Note that there are no scan data points within the shear pockets, so this dichotomy decision can be made easily.

(2) Generation of template image. Based on the as-designed dimensions of the specific structural feature to detect, a template image is generated. For example, Fig. 9(c) shows the template image representing shear pockets. The black square box in the center represents the shear pocket, and the surrounding white boundaries are added simply for better contrast of the template edges.

(3) Calculation of cross-correlation coefficient image. The cross-correlation coefficient image between the image representing scan data and the template image is obtained based on Equation (5) and is shown in Fig. 9(d).

(4) Estimation of locations of structural features. Pixels with high cross-correlation coefficients are selected and assigned with pixel values of one (i.e., in white color), as shown in Fig. 9(e). Then, these selected pixels are clustered using the region growing clustering technique (Adams and Bischof 1994) and the center of each cluster is defined as the center location of a detected structural feature.

(5) Corner extraction of structural features. After the center location of a structural feature is identified from the 2D image, the approximate edge positions of the structural feature are identified in the corresponding laser scan data. Then, all the edges of the structural feature are estimated from the laser scan data using the edge line estimation algorithm developed by Wang et al. (2016a), and the intersection points of the edge lines are defined as the corners of the structural feature, as shown in Fig. 9(f).

Fig. 10 shows another example, in which shear keys on the long side surface of a precast concrete panel are extracted from the laser scan data shown in Fig. 10(a). The unique characteristic of shear keys is that they have a depth difference from the plane of the side surface. Note that, because there are no scan points within flat ducts, shear keys and flat duct can be easily distinguished. Pixel values corresponding to the flat ducts (without any scan points) are assigned to zero (black color in Fig. 10(b)). The pixel values of all the other points within the side surface or the shear keys are linearly varied between 0.5 and 1 in proportion to the depth. Here, the depth is defined as the average distance of all scan points within the pixel to the least-square fitted plane of the side surface. Ideally, scan points inside the shear keys have pixel values of 0.5 because they have the smallest depth value, and scan points outside any structural features have grey scale values of 1 because they have the largest depth value. To locate shear keys, a template image is generated based on the as-designed dimensions of shear keys, as shown in Fig. 10(c). The center square box representing the shear key has a pixel value of 0.5, and the outer part has a pixel value of 1. The cross-correlation coefficient image is obtained as shown in Fig. 10(d), and the locations of two shear keys are identified in Fig. 10(e). The corners of the shear keys are then extracted in Fig. 10(f) using the technique developed in Wang et al. (2016a).

Extraction of Outer Boundaries

Here, the outer boundaries of the panel are extracted. Although each boundary should be a straight line for typical precast concrete panels, the as-built boundary may have manufacturing errors. Therefore, to represent an as-built boundary, a set of boundary points are extracted and the boundary is represented by simply connecting these boundary points.

The outer boundaries of a precast concrete panel can be classified into two types. The first type of boundaries refer to the intersecting boundary of two surfaces where scan data are available from both surface, such as the intersecting boundary between the top and the side surfaces shown in Fig. 11. On the other hand, the second type of boundaries only have scan data available only from a single surface without any scan data from the other surface. The bottom boundaries of side surfaces usually belong to the second type, because the bottom surface of a panel is often not scanned, such as the bottom boundary of the side surface shown in Fig. 12. Two different approaches are developed for each types as described below.

For the first type of boundary, the intersection line between two surfaces (the top and the side surfaces) is firstly extracted, shown as the dashed line in Fig. 11. Along this line, a set of points (*P1, P2…P11, P12* shown as crossings) are then selected with a certain interval q (depending on the required precision) as the locations for extracting boundary points. For each specific location (*P6*), a surface (*PL1*), which is crossing point *P6* and perpendicular to both the top and the side surfaces, is defined to indicate this location. Next, a local plane on the top surface (*PL2* shown in Fig. 11) is extracted as the least-square fitted plane of neighboring scan points on the top surface within a radius of $q/2$ around *P6*. Similarly, a local plane on the side surface (*PL3* shown in Fig. 11) is extracted. Finally, the boundary point at the location *P6* is extracted as the intersection point of the three planes (*PL1*, *PL2*, and *PL3*).

For the second type of boundary, the boundary points are extracted only from the side surface as shown in the bottom boundary of the side surface in Fig. 12. The scan data from the side surface are projected onto the 2D plane obtained by least-square fitting of all the scan data points from the side surface. The last point in each column (i.e., the point closest to the bottom edge) is extracted among the data points projected onto the 2D plane, and a line is estimated by least-square fitting all these points, as shown in the dashed line near the bottom boundary of the side surface in Fig. 12. Along this line, a set of locations (*P1′*, *P2′*…*P11′*, *P12′* shown as crossings) are selected with a certain interval q' (depending on the required precision) as the locations for extracting boundary points. The boundary point at each specific location is extracted in the following five steps.

Step 1: For a given location (location *P6′*), scan data points within a certain rectangular area surrounding *P6′* and also on the fitted 2D plan are first extracted, shown as blue dots (both empty and filled dots) in the zoom-in subfigure of Fig. 12. Here, the center of the rectangular area is positioned at Location *P6′*.

Step 2: From these extracted points, the last point in each column (i.e., the point closest to the bottom edge) is extracted and denoted as type I edge point (shown as filled blue dots).

Step 3: In each column, a type II edge point (shown as grey dots) is virtually created next to the type I edge point, assuming that the distance between two consecutive scan points is identical.

Step 4: A local edge line at the location *P6′* is estimated as a line maximizing the margins to type I and II scan points using a support vector machine (SVM) algorithm. A more detailed explanation of the SVM-based edge line estimation algorithm can be found in Wang et al. (2016a).

Step 5: The boundary point at location *P6′* is extracted as the center within the local edge line estimated within the rectangular area.

As-built BIM Creation

After the geometries of the target panel are extracted, an as-built BIM is created to store the geometries. To facilitate information exchange among different project stakeholders, a neutral BIM data format, namely Industry Foundation Classes (IFC) (buildingSMART 2016), is adopted. Specifically, the latest version of IFC, namely IFC4, is used in this study. Since the geometries of precast concrete panels are complex, the geometry is separated into multiple modules for modeling and all modules are then combined into a single BIM model, as illustrated in the following three steps.

(1) Define modules. For a typical precast concrete panel, each shear pocket, flat duct, and shear key is defined as one module. In addition, the panel itself excluding all the above-mentioned structural features is also defined as a separate module.

(2) Model individual modules. Each module is modeled using an instance of the IFC entity namely *IfcFacetedBrep*. An *IfcFacetedBrep* instance represents a solid as a collection of connected planar surfaces that delimit the solid from the surrounding non-solid. As shown in Fig. 13, the *IfcFacetedBrep* instance 1 representing a shear key is composed of six planar surfaces. Similarly, the *IfcFacetedBrep* instance 2 representing a cuboid panel excluding any structural features is also composed of six planar surfaces.

(3) Combine multiple modules. Two or more modules are combined using an instance of the IFC entity namely *IfcBooleanResult*. An *IfcBooleanResult* instance represents the result of a Boolean operation of two objects. Here, Boolean operation can be "union", "intersection", or "difference". The *IfcBooleanResult* instance shown in Fig. 13 is obtained as the "difference" of the two *IfcFacetedBrep* instances. The same approach can be used to model complex precast concrete panels with multiple structural features.

Lab-scale Experimental Validation

To validate the proposed technique, a lab-scale experiment was conducted. As shown in Fig. 14, a lab-scale specimen was manufactured using Styrofoam boards, with dimensions of 800 mm (length) × 260 mm (width) × 100 mm (height). The specimen had four shear pockets on the top surface with identical dimensions of 70 mm × 60 mm. On each long side, the specimen had two shear keys with dimensions of 60 mm × 60 mm and two flat ducts with dimensions of 60 mm × 40 mm, respectively. To facilitate further explanations, a local coordinate system was constructed by taking point O (in Fig. 14) as the origin and taking OA, OB, and OC vectors in Fig. 14 as the X, Y, and Z axes, respectively.

In the scan planning step, the threshold value α_t for the LOA criterion was set to 70° based on the study by Biswas et al. (2015), the threshold value s_t for the LOD criterion was set to 2 mm, and the angular resolution θ was set to 0.018°. All the surfaces except the bottom surface of the specimen needed to be scanned for as-built BIM creation. Since the scanner was mounted on a tripod and the tripod height could be adjusted from 0.5 m to 2 m, the height (i.e., Z value) of feasible scanner locations must be ranged from 0.5 m to 2 m. According to the scan planning result shown in Fig. 15(a), the optimal scanner locations included three locations, namely S1, S2, and S3. The locations were (1.2 m, 0.8 m, 1.5 m), (1.2 m, -0.8 m, 0.5 m), and (-0.4 m, 1 m, 0.5 m), respectively. The laser scan data were acquired using a FARO Focus 3D 120 terrestrial laser scanner, which had a ranging accuracy of ±2 mm within a distance of 20 m (FARO 2017). The scan data obtained from three scans were registered through coarse and fine registrations, as shown in Fig. 15(b). Afterwards, the as-built geometries of the specimen were extracted from the laser scan data, including the locations and dimensions of structural features and the outer boundaries of the specimen, as shown in Fig. 15(c). Last, the as-built BIM was created to represent the geometries of the specimen, as shown in Fig. 15(d).

To examine the accuracy of the proposed technique, the extracted as-built dimensions were compared to the actual dimensions, which were obtained from manual measurement using measurement tapes. Dimensions for comparison include the dimensions and locations of shear pockets, shear keys, and flat ducts, and the length, width and height of the specimen, as shown in Table 2. The dimensions of a shear pocket include the lengths of four boundaries of the shear pocket, resulting in a total of 16 dimensions for four shear pockets. The locations of a shear pocket include the distances from four boundaries of the shear pocket to the corresponding boundary of the specimen (e.g., the distance from the left boundary of the shear pocket to the left boundary of the specimen), resulting in a total of 16 locations for four shear pockets. Similarly, the dimensions and locations of four shear keys and four flat ducts include 16 dimensions, respectively. The length of the specimen was measured on the top surface at three different locations and on each long side surface at the center location, including a total of 5 measurements, as shown in Fig. 16. The width of specimen was measured on the top surface at eight different locations and on each short side surface at the center location, including a total of 10 measurements, as shown in Fig. 16. The height of specimen was measured on the each long side surface at eight different locations and on each short side surface at three different locations, including a total of 22 measurements, as shown in

Fig. 16. The numbers of length, width, and height measurements on different surfaces were determined based on the dimensions of the specimen. Generally, the length, width, and height of specimen were measured for every 100 mm. For example, since the length of the specimen was around 800 mm, eight (800/100=8) width measurements were conducted on the top surface. In addition, many locations for measuring the length, width, and height of the specimen were along the edges of structural features. This was to facilitate the measurement because the edges provided a baseline when measuring the dimensions.

As shown in Table 2, the averaged discrepancy (μ) between the dimensions from the proposed technique and those from manual measurement was ranged from 0.9 mm to 1.7 mm. The height of the specimen had the largest average discrepancy (1.7 mm). One possible explanation is that the bottom boundary of each side surface was estimated only from the scan data of the side surface because the bottom surface of the specimen was not scanned while all the other dimensions were estimated as the intersection of two surfaces. 122 (91.7%) out of all 133 measurements had discrepancies less than 2 mm. Considering that the LOD criterion was set to 2 mm, the proposed technique provided reasonable dimension estimations.

Full-scale Experimental Validation

To further validate the proposed technique, an experiment was conducted on a full-scale precast concrete bridge deck panel with dimensions of 12,600 mm × 2,480 mm × 240 mm, as shown in Fig. 17(a). The panel had 25 shear pockets with dimensions of 440 mm × 140 mm on the top surface. In addition, there were 23 shear keys with dimensions of 140 mm × 140 mm and 14 flat ducts with dimensions of 130 mm × 60 mm on each of the long side surfaces.

In the scan planning of the full-scale panel, all the settings (e.g., LOA criterion, angular resolution θ, and height of feasible scanner locations) were the same as the lab-scale experiment, except that the threshold value s_t for the LOD criterion was set to 5 mm considering that the tolerance value for precast concrete panel dimensions varies from 6 mm to 13 mm. As shown in Fig. 17 (b), the optimal scanner locations included six locations, denoted as S1, S2, S3, S4, S5, and S6. The coordinates of these locations are (6 m, -2 m, 2 m), (6 m, 5 m, 2 m), (-2 m, -3 m, 0.5 m), (14 m, -3 m, 0.5 m), (-2 m, 6 m, 0.5 m), and (14 m, 6 m, 0.5 m), respectively. Here, the coordinate system was constructed by taking the left bottom corner of the panel as the origin and taking the directions of the length, width, and height of the panel as the X, Y, and Z axes, respectively, as shown in Fig. 17(a). The scan data were acquired using the same scanner as the lab-scale experiment and the scan data were registered as shown in Fig. 17(c).

The as-built geometries of the precast concrete panel were extracted using the proposed technique. Fig. 18 illustrates the extraction of shear keys and flat ducts from the laser scan data of a long side surface. Note that the laser scan data shown in Fig. 18 are only a small part (around 2.6 m out of 12.6 m) of the whole long side surface. The laser scan data were first transformed into a 2D image, where pixels without scan points had black colors (pixel values of 0) and pixels with scan points were normalized into the range [0.5, 1]. Then, using the specific template images for shear keys and flat ducts, all the five shear keys and three flat ducts on the side surface were successfully detected. Based on the extracted geometries, an as-built BIM was created in IFC format, as shown in Fig. 19.

To validate the accuracy of the proposed technique, the extracted as-built dimensions of the panel from the proposed technique were compared to the actual dimensions, which were obtained from manual measurement. Similar to the lab-scale specimen, the dimensions used for comparison include the dimensions and locations of shear pockets, shear keys, and flat ducts, and the length, width and height of the panel, as shown in Table 3. Since it took too much time to manually measure all the dimensions, the dimensions were randomly sampled for manual measurement. For shear pockets, 12 out of 25 shear pockets were randomly selected for manually measuring their dimensions and locations. Similarly, 23 out of 46 shear keys and 14 out of 28 flat ducts were randomly selected for manual measurement. For the length, width, and height of the panel, a total of 12, 12, and 20 measurements were taken at different locations, respectively, as illustrated in Fig. 20. Note that the X, Y, and Z axes in Fig. 20 are shown in different scales for better illustrations.

As shown in Table 3, the averaged discrepancy (μ) between the dimensions from the proposed technique and those from manual measurement was ranged from 1.2 mm to 2.8 mm. Among all the 436 measurements, 402 (92.2%) of them had discrepancies less than 3 mm. Since the tolerance values for precast concrete panel dimensions mostly range from 6 mm to 13 mm according to Table 1, the 3 mm accuracy achieved by the proposed technique is sufficient enough to provide accurate dimension estimations supporting the dimensional quality assessment of precast concrete panels. Although manual inspection is able to achieve a similar accuracy given that each individual measurement is accurate, in reality, tedious work involved in manual inspection can make it error-prone and unreliable.

The developed technique not only provides more reliable quality inspection results compared to manual inspection, but also reduces time and labor costs for quality inspection. In the validation experiment, scan data acquisition took around 20 minutes and data processing took 4 minutes. Throughout the whole process, only one worker was needed to set-up the scanner and to run the program. On the other hand, it took two workers around 45 minutes to manually measure and record the 436 measurements, even though only sampling dimensions were measured. Note that two workers were needed because some dimensions were too long to be measured by only one worker. It is estimated that manually measuring all the dimensions can take two workers more than

90 minutes, indicating that the proposed technique can reduce the manpower cost for quality inspection by 86.7%. Therefore, the results demonstrate that the proposed technique can provide much more efficient dimension estimation compared to manual measurement.

Conclusions

The quality assessment of precast concrete panels has been relying on manual inspection, which is not only subjective and unreliable, but also time-consuming and labor-intensive. In addition, the quality assessment results are currently stored in traditional ways such as paper sheets or Excel spreadsheets, making it difficult to visualize and manage the as-built geometries of panels. Although previous research efforts have been reported on laser scanning based quality inspection of precast concrete panels, these efforts focused on only one surface of a panel, were dependent on the as-designed BIM, and did not store the as-built geometries in a BIM model. To tackle these limitations, this study proposes a technique for automatic creation of as-built BIM of precast concrete panels using laser scan data. A fully automatic algorithm is developed to extract the as-built geometries of precast panels from the laser scan data, which enables more accurate and efficient geometry extraction and quality assessment. The algorithm is able to estimate the as-built dimensions for an entire panel and to extract the locations of certain structure features based on only the as-designed dimensions of the features. Furthermore, the extracted geometries of the panel are then stored in a BIM model, which facilitates the visualization and management of the as-built geometries.

To validate the proposed technique, experiments on a lab-scale specimen and a full-scale precast concrete panel were performed. For the full-scale panel, when compared with the dimensions obtained from manual measurement, 92.2% of the dimensions estimated by the proposed technique had discrepancies less than 3 mm, which is accurate enough for assessing the dimensional quality of precast concrete panels considering the allowable tolerances (6 mm to 13 mm). Although manual inspection can achieve a similar accuracy given that individual measurement is accurate, manual inspection results can be unreliable due to tedious works involved. In addition to accuracy and reliability, the dimension estimation by the proposed technique took only 24 minutes by a single worker, much less than the time necessary for manual measurement (90 minutes for two workers). The manpower cost for quality inspection was reduced by 86.7% using the proposed technique. To conclude, the experiments demonstrate that the proposed technique can estimate dimensions and create as-built BIM for precast concrete panels in an accurate and efficient manner.

This study still has a few limitations. First, LOA and LOD constraints in the scan planning step still need manual inputs. Future research is warranted for automatic extraction of such constraints from construction codes. Second, the scan data acquisition still requires manual maneuvering of the laser scanner to different locations. Vehicle-borne laser scanning or air-borne laser scanning can be adopted for further automation of data acquisition. Third, the proposed technique has been tested only in a controlled environment. On real construction sites, it will be often challenging to place the scanner at desired locations to ensure certain data quality and to avoid occlusions. An alternative in the future might be to employ air-borne laser scanner although the accuracy has much room for improvement at this point.

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Tables

Table 1. Part of the checklist for precast concrete bridge units (Gutt et al. 2000)

Item	Tolerance
Length/width of panel	±6 mm
Depth of panel	+6 mm, -3 mm
Dimensions of structural features (shear pockets, shear keys, ducts)	±6 mm
Locations of structural features (shear pockets, shear keys, ducts)	±6 mm
Strand projection from end	±13 mm
Stirrup project from surface	±13 mm
Longitudinal spacing of stirrups	±25 mm

Table 2. Average difference (μ) between the dimensions estimated by the proposed technique and those from manual measurement for the lab-scale specimen.

Dimension	**Description**	**Number**	$\boldsymbol{\mu}$ **(mm)**
Dimensions of shear pockets	Four boundaries of each shear pocket (4) × the number of shear pockets (4)	16	1.3
Locations of shear pockets	From four boundaries of each shear pocket to the corresponding specimen boundary (4) × the number of shear pockets (4)	16	1.2
Dimensions of shear keys	Four boundaries of each shear key (4) × the number of shear keys (4)	16	0.9

Locations of shear keys	From four boundaries of each shear key to the corresponding specimen boundary (4) × the number of shear keys (4)	16	1.2
Dimensions of flat ducts	Four boundaries of each flat duct (4) × the number of flat ducts (4)	16	0.9
Locations of flat ducts	From four boundaries of each flat duct to the specimen boundaries (4) × the number of flat ducts (4)	16	1.3
Length of specimen	Length measurement on the top surface (3) + length measurement on each long side (1×2)	5	1.0
Width of specimen	Width measurement on the top surface (8) + width measurement on each short side (1×2)	10	1.3
Height of specimen	Height measurement on each long side (8×2) + height measurement on each short side (3×2)	22	1.7

Table 3. Average difference (μ) between the dimensions estimated by the proposed technique and those from manual measurement for the full-scale panel.

Dimension	**Description**	**Number**	**μ (mm)**
Dimensions of shear pockets	Four boundaries of each shear pocket (4) × the number of selected shear pockets (12)	48	2.0
Locations of shear pockets	From four boundaries of each shear pocket to the corresponding panel boundary (4) × the	48	1.6

	number of selected shear pockets (12)		
Dimensions of shear keys	Four boundaries of each shear key (4) × the number of selected shear keys (23)	92	1.2
Locations of shear keys	From four boundaries of each shear key to the corresponding panel boundary (4) × the number of selected shear keys (23)	92	1.7
Dimensions of flat ducts	Four boundaries of each flat duct (4) × the number of selected flat ducts (14)	56	1.5
Locations of flat ducts	From four boundaries of each flat duct to the corresponding panel boundary (4) × the number of selected flat ducts (14)	56	2.0
Length of panel	Length measurement on the top surface (10) + length measurement on each long side (1×2)	12	2.2
Width of panel	Width measurement on the top surface (10) + width measurement on each short side (1×2)	12	1.6
Height of panel	Height measurement on each long side (5×2) + height measurement on each short side (5×2)	20	2.8