Noncontact Quality Assessment of Precast Concrete Elements using 3D Laser Scanning and Building Information Modeling

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Noncontact Quality Assessment of Precast Concrete Elements using 3D Laser Scanning and Building Information Modeling
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A dissertation submitted to the faculty of KAIST in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Civil and Environmental Engineering. The study was conducted in accordance with Code of Research Ethics¹.

2014. 11. 28
Approved by
Professor Hoon Sohn

¹Declaration of Ethical Conduct in Research: I, as a graduate student of KAIST, hereby declare that I have not committed any acts that may damage the credibility of my research. These include, but are not limited to: falsification, thesis written by someone else, distortion of research findings or plagiarism. I affirm that my thesis contains honest conclusions based on my own careful research under the guidance of my thesis advisor.
레이저 스캐닝 및 빌딩 정보 모델링을 활용한 비접촉식 프리캐스트 콘크리트부재 폼질평가

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ABSTRACT

As precast concrete based rapid construction becomes more commonplace and standardized in the construction industry, checking the conformity of dimensional and surface qualities of precast concrete elements to the specified tolerances has become ever more important to prevent construction failures. Moreover, as BIM gains popularity due to increasing demand for information technology (IT) in the construction industry, autonomous and intelligent QA techniques that are interoperable with BIM and a systematic data storage and delivery system for dimensional and surface QA of precast concrete elements is urgently needed. The current method for dimensional and surface QA of precast concrete element relies largely on manual inspection and contact-type measurement devices, which are time consuming and costly. To overcome the limitations of the current precast concrete QA method, this study aims to develop intelligent precast concrete QA techniques based on 3D laser scanning and BIM technology. There are four research cores investigated in this study, which are (1) dimensional and surface QA techniques, (2) BIM based QA data storage and management framework (3) scan parameter optimization for accurate QA and (4) validation through field tests.

Two QA techniques are developed in this study. Firstly, a non-contact measurement technique that automatically measures and assessed the dimensional qualities of precast concrete elements is developed using a 3D laser scanner. A robust edge extraction algorithm, which is able to extract only the scan points within the edges of a target precast concrete element, is developed based on a unique characteristic of scan points captured from the laser scanner. Moreover, to increase the dimensional estimation accuracy, a compensation model is employed to account for the dimension losses caused by the mixed pixel problem of laser scanners. Experimental tests on a lab scale specimen as well as lab scale actual precast concrete elements are performed to validate the effectiveness of the proposed technique. Secondly, a surface QA technique that simultaneously localizes and quantifies surface defects on precast concrete surfaces is developed. Defect sensitive features, which have complementary properties to each other, are developed and combined for improved localization and quantification of surface defects on precast concrete elements. A defect classifier is also developed to automatically determine whether the investigated surface region is damaged, where the defect and its size is located. To validate the robustness of the proposed surface QA technique, numerical simulations and experiments are conducted.
For data storage and management for QA of precast concrete elements, a BIM-based data storage and management framework is proposed. The framework aims to answer four essential questions for precast concrete QAs, which are (1) what the inspection checklists should be; (2) what the quality inspection procedure should be employed; (3) which kind of laser scanner is appropriate and which scan parameters are optimal for the intended quality inspection; and (4) how the inspection data should be stored and delivered. The feasibility of the proposed framework for dimensional and surface QA of precast concrete elements is investigated through case studies where dimensional errors and surface defects within lab-scale precast slabs are detected and those QA data are systematically stored and managed with help of BIM.

In scan parameter optimization, a method of selecting optimal scan parameters of a laser scanner is proposed to ensure that the proposed dimensional QA technique provides satisfactory accuracy. It was found in the experimental results of the previous study that dimensional estimation accuracy is largely influenced by scan parameters, especially in the incident angle between the laser scanner and target object. Hence, to find optimal scan parameters for dimensional QA, a simulation model that estimates the laser beam position of the laser scanner is developed by constructing the geometric position of the laser beam and contaminating the measurement noise of the laser beam into the mathematical laser beam position. Comparison tests with experiments are conducted to validate the laser beam model, and parametric studies with different scan parameters are implemented based the developed model to find optimal scan parameters.

Finally, this research validates the effectiveness of the proposed QA techniques and the data storage and management system through field tests. In the field test, two types of full-scale precast concrete slabs with complex geometries are scanned in a precast concrete factory and dimensional QA checklists including dimension and positions are inspected. The challenges encountered during the data analysis of the full-scale test are discussed and addressed. In addition, a comparison test with the conventional deviation analysis is conducted and the robustness of the developed dimensional QA technique is demonstrated. Furthermore, a cloud-BIM web-service is employed to investigate the potential of the proposed data storage and management system for QA of precast concrete elements.

**Keywords:** 3D laser scanning, building information modeling (BIM), dimensional quality assessment, precast concrete element, surface quality assessment
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1 INTRODUCTION

1.1 Research Background

1.1.1 Precast concrete element based rapid construction

The construction industry is typically characterized by labor intensity technology, hard labor conditions, low productivity, and high risks (Kazaz and Ulubeyli 2008). According to the UNEP (UNEP Report 2002), these problematic conditions mainly result from the slow integration of technological advances and industrialization principles such as computer-aided construction, automation, standardization and modularization. Precast concrete element based construction is one construction method that uses the principles of industrialization in the construction process. Over the last few decades, precast concrete elements have become a popular component for construction projects such as low- and mid-rise apartments, office buildings and bridges (Figure 1.1). According to a survey (Arditi et al. 2000), they are employed all over the globe, especially in many European countries including the United Kingdom, Netherlands and Italy. It was reported that the market share of precast concrete element based construction across the European Union (EU) is between 20-25%, and is 40-50% in northern European countries (YEMAR Report 2006).

Precast (also known as ‘prefabricated’) literally means that structural concrete components such as slabs and columns are standardized and manufactured in a certain facility by casting concrete in a mold or “form”. It is then cured in a controlled environment and transported to the construction site for assembly (Allen 2009). Utilizing precast concrete elements offers potential advantages over conventional cast-in-place concrete components, which can be summarized as follows: (1) Reduced time and labor cost - compared to site-cast (or in-situ) construction, precast concrete elements offer faster production, lower cost, and more efficient assembly of elements since they provide an opportunity to complete tasks in parallel (Sack et al. 2004; Yee 2001; Pheng and Chuan 2001; Bilsmas et al. 2006). It was reported that when in-situ concrete casting panels were replaced with prefabricated elements, 70% of construction time and 43% of labor costs could be saved (Wong et al. 2003; Jaillon et al. 2009); (2) Improved work zone safety - construction sites often require workers to operate at high elevations or in potentially risky situations. Since the production process of precast concrete elements is performed on ground level, conditions throughout the project is safer; (3) Minimized traffic disruption during the construction of bridges - in contrast with cast-in-place concrete bridge
construction that causes significant traffic disruption due to numerous and sequential on-site construction procedures such as concrete cast and curing processes, precast concrete elements allows for the moving of those construction procedures away from the construction site and traffic; (4) Increased constructability - since concrete components are mass produced in well-controlled environments, they offer consistent mechanical properties, resulting in an increase of constructability for a construction project; and (5) Reduced environmental impacts - the use of precast concrete components also leads to a much cleaner and safer construction environment since fewer materials are wasted during the production and erection processes of precast products for a construction project (Tam et al. 2007).

1.1.2 Quality assessment of precast concrete elements

Despite the various benefits of precast concrete element based rapid construction, the use of precast concrete elements, however, could suffer from unexpected construction delays and system failures if the dimensional and surface qualities of precast concrete elements are not assessed properly. For instance, construction delays and additional costs for repair or replacement are unavoidable when there are serious dimensional mismatches or volumetric surface defects on precast concrete elements (GDT Report 2011). Research conducted by the Construction Industry Institute (CII) revealed that the average cost of rework caused by construction defects is 5% of total construction costs (Construction Industry Institute Report 2005). Mills et al. (2009) also indicated defect costs accounted for 4% of the contract value of new residential construction. According to a study (Love and Li 2000) that examined the causes of rework, systematic quality assessment (QA) and found that management for construction components during the design and construction phases are important in reducing or

Figure 1.1 Utilization of precast concrete elements in the construction industry: (a) Buildings; (b) Bridges
eliminating rework in projects. As a result, a systematic dimensional and surface QA for precast concrete elements at an early stage of construction process is essential for the successful and timely completion of a construction project.

Currently, the quality of precast concrete panels is evaluated manually assessed by certified inspectors. The inspectors rely on contact-type devices such as measuring tapes and straightedges for QA of precast concrete elements (Latimer et al. 2002), and follow guidelines such as the quality management system from the International Organization for Standardization (ISO-9001 2008) or the tolerance manual for precast and prestressed concrete from the Precast Concrete Institute (PCI 2000). One of the main inspection objectives is to scrutinize dimensional (dimension, position etc.) errors and surface defects (crack, spallings etc.) of precast concrete elements. However, there are several problems with manual inspection. Firstly, the results obtained are subjective and may not be reliable (Phares et al. 2004). Second, manual inspection is time consuming and expensive. Third, there is a lack of trained and experienced inspectors. Finally, there is a lack of data storage and management system necessary for effective and efficient information sharing and management between the participants of a construction project. Therefore, there is an urgent need for techniques that access and manage the dimensional and surface qualities of precast concrete elements in an automated and accurate manner.

1.2 Literature Review

1.2.1 Non-contact sensing based quality assessment

Dimensional and surface QAs have been mainly studied in the industrial engineering sectors for the purpose of faultless goods production (Newman and Jain 1995). In most cases, inspections are conducted using image processing techniques involving one or more cameras, and the scene is illuminated and arranged to extract the image features necessary for processing and classification. However, these studies are limited to relatively small objects and the inspection environment is well controlled, which is not possible for the in-situ inspection of precast concrete elements.

In the Architecture, Engineering and Construction (AEC) sector, many researchers have explored non-contact sensing techniques to monitor the dimensional and surface qualities of structures during the last decade. Among the non-contact sensing technologies, the use of images obtained from 2D cameras is one of the most common approaches to detect dimensional errors or surface defects
because it is fast and inexpensive. In terms of the dimensional QA, Ordonez et al. (2008) proposed two different image-based approaches for detecting and measuring the dimensions of flat building elements. Shin and Dunston (2009) presented an augmented reality method for the steel column inspection (anchor bolt positions and plumbness). These approaches, however, require significant human interaction for the dimensional inspections. With regards to the surface QA, the majority of studies have focused on the detection of cracks, air-pockets and spallings. Abdel-Qader et al. (2006) suggested a concrete crack detection technique using the principal component analysis for the purpose of autonomous bridge inspections. Hutchinson and Chen (2006) proposed a probabilistic method based on Bayesian decision theory for automatic crack detection on concrete surfaces. Zhu and Brilakis (2010) suggested the use of three circular filters to detect air pockets on the surfaces of concrete. Koch and Brilakis (2011) proposed a technique using image segmentation and morphological thinning to detect spalling defects on concrete surfaces. While these image-based methods generally offer good measurement accuracy, their performance is heavily affected by lighting conditions. In addition, although identification of size information such as length, width, area and volume is important for the dimensional and surface QA of concrete structures, this kind of qualitative information cannot be gained using image-based methods without multiple cameras (at least two) or prior knowledge such as the distance between a camera and a target structure or the size of a reference target.

Contrary to the digital imaging approach, laser scanning directly acquires 3D data with good accuracy (typically 2-6 mm at 50 m (Olsen et al. 2010)) and high point density (up to 960,000 points/sec (FARO 2014)). Due to these merits, several researchers have investigated the feasibility of laser scanning technology for the dimensional and surface QA of structures during the last decade. With regards to the dimensional QA, Bosche (2010) proposed an automated technique of recognizing 3D CAD objects from laser-scanned data for dimensional compliance inspection of construction elements. Shih and Wang (2004) reported a laser scanning-based system for measuring the dimensional quality of finished walls. Akinci et al. (2006) proposed a general framework for quality inspection of structures based on comparison of as-built models obtained from laser scanning with the corresponding design CAD models. Han et al. (2013) suggested an automated technique of extracting tunnel cross sections using laser-scanning data for dimensional quality control. Gordon et al. (2007) and Park et al. (2007) reported deformation measurement results obtained from laser scanners for dimensional quality control of structures. In terms of the surface QA, Teza et al. (2009) proposed a
damage detection technique based on the computation of the mean and Gaussian curvatures of a concrete surface. Tang et al. (2011) investigated the detectability of surface flatness defects using damage detection algorithms and laser scanners. Olsen et al. (2010) proposed a volume loss quantification technique for a reinforced concrete structure. Lastly, Liu et al. (2011) proposed a distance and gradient-based volume loss estimation technique for an in-situ concrete bridge. Although laser-scanning data has been widely utilized for the dimensional and surface QA in variety of civil applications, there have been no studies utilizing laser scanning for dimensional and surface QA of precast concrete elements.

1.2.2 Data storage and delivery for quality assessment

The current data storage and delivery for QA of precast concrete elements follows the following procedure (Yin et al. 2009): (1) certified inspection personnel monitors and records the inspection results of specified checklists in the inspection form and (2) once the QA is completed, the inspector stores the inspection data of the inspection form into a database system via a computer. The current data storage and delivery system, however, has limitations. First, it is inefficient due to the duplicated process of recording the inspection data in both document from and the database. Second, there is a possibility of data entry error and inspection form loss. Moreover, there are difficulties in interactively updating and sharing the inspection data with other project participants who work in different places.

Building Information Modeling (BIM) is a conceptual approach to computer-intelligible exchange of building information in design, construction and other disciplines (Sack et al. 2010). Note that more details behind BIM are described in Chapter 1.4.2. Several recent studies have explored the possibility of a BIM-based system for effective data storage and management. The majority of those studies have focused on solving frequently occurring data exchange problems in construction projects due to the diversity of construction participants. Jeong et al. (2009), for example, tested various BIM tools such as Revit Architecture (2014) from Autodesk Inc. and Tekla Structures from Tekla Inc. (2014) to identify the interoperability of BIM data such as geometric shapes and relationship information of precast concrete elements. The study concluded that the Industry Foundation Classes (IFC) is the only candidate for the effective exchange of geometry and other information among various data formats, but current IFC-based data exchanges remains lacking in data exchanges between BIM tools. To this end, Venugopal et al. (2012) proposed an IFC based
framework to facilitate data exchange and avoid ambiguity in IFC information for precast/pre-stressed concrete elements. The study recommended that definitions of entities, attributes and relationships of precast concrete models needs to be clearly defined for reliable data exchanges. Aram et al. (2013) proposed a process model for identifying the necessary capabilities of BIM tools for supporting and improving the entire data exchange of concrete reinforcement supply chain. However, the aforementioned studies mainly focus on data interoperability of design models of precast concrete elements, with less attention paid to storing and delivering dimensional and surface QA data of precast concrete elements.

Regarding the representation of QA data obtained from non-contact sensors, Yin et al. (2009) proposed a precast production management system based on Radio Frequency Identification (RFID). Several quality inspection targets, such as material property and production process, were monitored in that system, but the dimensional and surface qualities are not studies and thus, there is no standard data format for the system. Anil et al. (2011) investigated the data representation requirements of as-built BIM generated from laser scanned point cloud data. The study found that there is no formalized schema for representing the quality of as-built BIM such as model deviations and noises in the current version of IFC. Hence, a formalized and systematic data storage and delivery method for representing the dimensional and surface QA of precast concrete elements is necessary. In this study, an IFC-based data storage and delivery system is proposed for dimensional and surface QA of precast concrete elements.
1.3 Research Objectives and Scope

To tackle the limitations of current QA techniques, the goal of this research is to develop smart QA techniques and a system for precast concrete elements using 3D laser scanning and BIM technology. Specifically, this study has four main objectives: (1) Development of dimensional and surface QA techniques; (2) Development of a framework for systematic precast concrete QA; (3) Optimization of scan parameters for enhanced precast concrete QA; and (4) Validation of the proposed technique and system through field test. The scope of this dissertation is as follows:

1. Development of dimensional quality assessment technique: This study develops an automated and non-contact measurement technique that measures and assesses the dimensions and the quality of precast concrete elements using a 3D laser scanner. An edge and corner extraction technique is developed to estimate the dimensional properties of precast concrete elements from laser scanning data. To increase the measurement accuracy, a compensation model is employed to account for the dimension losses caused by an intrinsic limitation of laser scanners. Experimental tests are performed on a laboratory specimen and actual precast concrete elements to validate the effectiveness of the proposed technique.

2. Development of surface quality assessment technique: This study develops a new technique that can simultaneously localize and quantify spalling defects on precast concrete surfaces using a laser scanner. Defect sensitive features, which have complementary properties, are developed and combined for improved localization and quantification of spalling defects. A defect classifier is developed to automatically diagnose whether the investigated surface region is damaged, as well as the location and size of the defect. Numerical simulations and experiments are conducted to demonstrate the effectiveness of the proposed concrete surface defect detection technique. Furthermore, a parametric study with varying scan parameters is performed for optimal detection performance.

3. Development of BIM-based systematic framework of QA data management: This study develops a holistic framework for dimensional and surface QA of precast concrete elements based on BIM and 3D laser scanning technology. Here, the term ‘holistic’, as used in this paper, refers to the ‘end-to-end’ from actual dimensional and surface QA to storage and management of the inspection data. First, a framework is developed to answer four essential questions for practical precast concrete QA: (1) what the inspection checklists should be; (2) what quality inspection procedures should be employed; (3) which kind of laser scanner is appropriate and which scan parameters are optimal for
the intended quality inspection; and (4) how the inspection data should be stored and delivered. Then, the applicability of the proposed framework is evaluated using case studies where dimensional errors and surface defects within actual precast concretes are detected and measured.

(4) Optimization of scan parameters: This study proposes a method of ensuring the accuracy of the proposed dimensional and surface QA techniques. It was found from the experimental studies in the previous study that enhancement of dimensional estimation accuracy is essential for success of actual applications. The objective of this study is to improve the dimensional quality assessment technique through scan parameter optimization. To do this, a modeling the laser beam position and the measurement errors of the laser scanner is conducted, and parametric studies with different scan parameters are implemented with the developed model. Comparison tests with experiments are also investigated to determine the effectiveness of the proposed scan parameter optimization method.

(5) Validation through field tests: This study investigates the feasibility of the proposed quality assessment system of precast concrete elements through field tests. The developed dimensional quality assessment technique is further advanced so that this technique can also be applied to full-scale precast concrete elements with complex geometries. In the field test, two types of full-scale precast concrete slabs with complex geometries are scanned in a precast concrete factory and dimensional QA checklists including dimension and positions are inspected. The challenges encountered during the data analysis of the full-scale test are discussed and addressed. In addition, a comparison test with the conventional deviation analysis is conducted and the robustness of the developed dimensional QA technique is demonstrated. Furthermore, a cloud-BIM web-service is employed to investigate the potential of the proposed data storage and management system for QA of precast concrete elements.
1.4 Research Means

1.4.1 3D laser scanning technology

Developments in Information Technology (IT) have provided opportunities for the AEC industry, one of which is 3D laser scanning technology. 3D laser scanning is a relatively new technology, first developed for surveying engineering. The principle of 3D laser scanning is that a laser scanner moves rapidly along both horizontal and vertical directions and captures the distance, azimuth, and altitude information of multiple points on a target structure. These scanned points are called ‘point cloud data’, and their positions are defined in a 3D spherical coordinate system. The azimuth and altitude information is recorded by the laser scanner as it rotates, and the distance is measured by two different principles: time-of-flight (TOF) and phase-shift. Laser scanners using the TOF principle send out an initial laser pulse signal, and measures the arrival time of the laser beam reflected from a target point. The distance to the target point is then computed based on the laser travel time and the laser velocity. Laser scanners with phase-shift emit a continuous sinusoidal laser beam, and estimates the distance by measuring the phase difference between the emitted and reflected.

![Figure 1.2 Working principles of 3D laser scanners: (a) Time-of-flight scanners; (b) Phase-shift scanners](image-url)
sinusoidal laser beams. Typically, TOF scanners have a relatively slow measurement speed and are used for long-range scanning (typically 4-10 mm (one sigma value) accuracy at a distance of 50 m (Olsen et al. 2010)). On the other hand, phase-shift laser scanners have a faster measurement speed and are suitable for a short-range scanning (2-4 mm (one sigma value) accuracy at a distance less than 20 m (FARO 2014)).

Compared to conventional contact-type sensors used in the AEC industry, a 3D laser scanner provides the following advantages: (1) It allows the quick scanning of a large structure and measurement of a surface profile; (2) It yields ‘point cloud’ data of a scanned target surface with millimeter-level accuracy and spatial resolution; and (3) It offers long-range measurement up to 6000 m (REIGL 2014). In addition, as shown in Table 1.1, 3D laser scanning has advantages over the other two 3D measurement technologies (stereo-vision camera and TOF camera) in (1) accuracy, (2) measurement range, (3) measurement angle, and (4) resolution. Note that for each 3D measurement technology, the specification of the most common commercial device is provided. With these features, 3D laser scanners have been successfully employed for a wide variety of applications, including 3D modeling of structures (Bernardini and Rushmeier 2002; Son et al. 2002), deflection and deformation monitoring (Park et al. 2007), construction progress monitoring (Kim et al. 2013) and topographical surveys (Priestnall et al. 2000).

Table 1.1 Comparison of technical specifications of 3D measurement sensors.

<table>
<thead>
<tr>
<th>Property</th>
<th>3D laser scanner (Ex. FARO Focus-3D)</th>
<th>Stereo Camera (Ex. Point-Grey Bumblebee2)</th>
<th>TOF Camera (Ex. MESA SR4000)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>± 2 mm @ 20 m</td>
<td>± 2 mm @ 2 m</td>
<td>± 20 mm @ 5 m</td>
</tr>
<tr>
<td>Measurement range</td>
<td>0.6 ~ 120 m</td>
<td>~ 4 m</td>
<td>0.1 ~ 10 m</td>
</tr>
<tr>
<td>Measurement angle</td>
<td>Hori. 360° / Vert. 310°</td>
<td>Hori. 66° / Vert. 43°</td>
<td>Hori. 44° / Vert. 35°</td>
</tr>
<tr>
<td>Measurement speed</td>
<td>960,000 points / sec</td>
<td>48 frames / sec</td>
<td>30 frames / sec</td>
</tr>
<tr>
<td>Resolution</td>
<td>Depends on angular resolution</td>
<td>Pixels 648 × 488</td>
<td>Pixels 176 × 144</td>
</tr>
</tbody>
</table>
1.4.2 Building information modeling (BIM)

Figure 1.3 Conceptual diagram of Building Information Modeling (BIM)

Another leading piece of IT in the AEC industry is BIM. According to the National BIM Standard (NBIMS) Project Committee of the BuildingSMART alliance (2014), BIM is defined as ‘a digital representation of physical and functional characteristics of a facility’. As depicted in Figure 1.3, BIM serves as a central data repository that stores and recalls information about a facility, and is currently regarded as an essential tool in managing the lifecycle of a construction project from initial design to maintenance (Hajian and Becerik-Gerber 2009). Due to these abilities in enhancing communication between the various stakeholders involved in the different stages of a facility's life cycle and the multitude of potential uses ranging from improved planning for renovations to more accurate modeling of a building's energy consumption (GSA 2009), BIM is gaining attention in the Architecture, Construction, Engineering, and Facility Management (AEC/FM) community. Adoption has been rapid, with nearly half of AEC professionals implementing BIM, an increase of 75% in the past two years (McGraw-Hill Construction 2009). Unlike a traditional CAD model that is mainly used for visualization, BIM represents a facility in a semantically rich manner. For example, while a CAD
model would represent a wall as a set of independent planar surfaces, BIM would represent the wall as a single, volumetric object with multiple surfaces, while also showing the adjacent relationships with other components in the model (Tang et al. 2010). Because of this unique characteristic of BIM, working environment of the AEC industry is shifting from 2D-based information platforms to object-based 3D information platforms. Moreover, the advent of BIM has allowed the participants of a project to more effectively share and update information generated during the construction process in a timely manner, producing a synergy effect.

Combining laser scanning with BIM can yield significant advantages over traditional approaches by facilitating design and construction activities on the basis of accurate, fully representative existing conditions captured with laser scanners (Randall 2011). The approach of integrating as-built and as-designed data sets enhances the efficiency of information management and results in improved reliability of the project model (Goedert and Meadati 2008). Coming from the advantages of integrating two IT methods, recently conducted studies have taken advantage of this integration in the AEC industry. As an example of this trend, General Services Administration (GSA 2009) documented BIM guidance for 3D imaging, intended for assisting the project teams in contracting for and ensuring quality in 3D imaging contracts.
1.5 Organization

This document is organized as follows:

Chapter 2 presents the dimensional QA technique as one of the precast concrete QA techniques. Data processing algorithms, including an edge and corner extraction technique, are described for the estimation of the dimensional properties of precast concrete elements from laser scanning data. In addition, a compensation model, which compensates the dimension losses caused by the ‘mixed-pixel’ problem of 3D laser scanners, is discussed to increase the measurement accuracy. Lastly, validation tests on a laboratory specimen as well as actual precast concrete elements are presented to prove the effectiveness of the proposed dimensional QA technique.

Chapter 3 deals with the surface QA technique that simultaneously localizes and quantifies surface defects on precast concrete surfaces using a laser scanner. Defect sensitive features and a defect classifier utilized for surface defect detection are discussed. The results of numerical simulation and experiments on a lab-scale actual precast concrete are presented to demonstrate the effectiveness of the proposed surface QA technique of precast concrete elements.

Chapter 4 presents the framework for dimensional and surface QA of precast concrete elements based on BIM and 3D laser scanning technology. The framework answers four essential questions for practical precast concrete QA in terms of (1) what the inspection checklists should be; (2) what the quality inspection procedure should be employed; (3) which kind of laser scanner is appropriate and which scan parameters are optimal for the intended quality inspection; and (4) how the inspection data should be stored and delivered. In addition, case studies for investigating the applicability of the proposed framework are presented.

Chapter 5 presents the scan parameter optimization technique to guarantee satisfactory dimensional QA accuracy. To do this, a modeling of the laser beam position and measurement errors of the laser scanner is conducted, and parametric studies with different scan parameters are implemented using the developed model. Comparison tests with experiments are also investigated to identify the effectiveness of the proposed scan parameter optimization method.

Chapter 6 discusses the feasibility of the proposed quality assessment system of precast concrete elements through field tests. The developed dimensional QA technique is applied to full-scale precast concrete elements with complex geometries. A comparison test between the proposed dimensional QA technique and a conventional deviation analysis technique is presented.

Chapter 7 summarizes this document with expected contributions, and presents future work associated with this research.
2 QUALITY ASSESSMENT TECHNIQUE I: DIMENSIONAL ESTIMATION

2.1 Chapter Introduction

A dimensional QA technique for precast concrete elements is presented in this chapter. The main checklists for the dimensional QA of precast concrete elements include their dimensions (length, width and thickness), squareness, straightness and flatness as shown in Fig. 2.1. To tackle the limitations of the conventional dimensional QA method, this chapter presents an automated technique that allows accurate and reliable dimensional estimation of precast concrete elements using 3D laser scanning. To measure the length, width and squareness of the precast concrete elements, a novel edge extraction algorithm is developed so that only boundary points of a precast concrete element are automatically extracted from the point cloud obtained by a 3D laser scanner. To validate the dimensional QA technique, experiments on a laboratory specimen as well as actual precast concrete elements are were conducted. The results demonstrate that the proposed dimensional QA technique has potential in automatically and accurately assessing dimensional qualities including dimensions, positions and squarenesses. This chapter is organized as follows. First, related literatures are presented in Chapter 2.2, followed by development of the dimensional QA technique in Chapter 2.3. Then, a series of laboratory tests for investigation of various scan parameter effects are discussed in Chapter 2.4, and actual experimental results implemented on real precast concrete slabs are presented in Chapter 2.5. The chapter then concludes with a summary in Chapter 2.6.

![Figure 2.1](image)

**Figure 2.1** Dimensional quality assessment of precast concrete elements: (a) Dimensions; (b) Squareness; (c) Straightness; (d) Flatness.
2.2 Related Work

2.2.1 Surface reconstruction using point cloud data

Over the past few decades, many studies have been conducted in computer graphics regarding geometric data analysis based on laser scanners. The main purpose of these approaches is to improve surface reconstruction of an object based on dense laser scan data (Hoppe et al. 1992; Althaus and Christensen 2003; Dey 2007). Most surface reconstruction methods employ triangle meshes to model geometric surface information of a physical object, and mainly focus on improving the smoothness of the object surface. However, the target objects of these studies are limited to small objects, and the point clouds acquired from triangulation-based laser scanners allow for only very short scan range (less than 5 m). In civil engineering, several techniques have been proposed for modeling of building facades with help of long-range measurement from laser scanners. Pu and Vosselman (2009) presented a feature extraction technique using point cloud data with the purpose of building façade modeling. This method uses knowledge about the building façade to segment the point cloud and match the data with building feature constraints. Becker and Haala (2007) proposed a building façade reconstruction method by integrating point cloud data and digital photos. However, these approaches focus on modeling building façade features such as windows and doors, which gives no quantitative dimensional measurements of building components.

2.2.2 Three-dimensional edge detection

3D edge detection has been mainly studied in the computer graphics community. The majority of the work finds edges or lines from polygonal mesh models or point cloud data (Ohtake et al. 2004; Truong-Hong et al. 2012; Gumhold et al. 2001; Pauly et al. 2003). As for the polygonal mesh model, Ohtake et al. (2004) searched edge lines of an object based on curvature derivatives of the mesh model. Truong-Hong et al. (2012) presented a boundary feature detection algorithm for recognition of building facades using point cloud data. This method employs Delaunay triangulation meshes to find boundary points and uses a grid clustering technique to determine the boundary lines of widow openings. The result provides relative geometric errors of 1.2-3.0% for building facades and open windows when compared with CAD-based models. However, the average absolute geometric errors are over 20 mm, which is not acceptable for precast concrete dimensional QA requiring small tolerances (± 6 mm for precast slabs). As for the edge detection from point cloud data, Gumhold et al.
(2001) developed an edge line extraction method using local neighbor graph theory for surface reconstruction. Pauly et al. (2003) proposed a technique for extracting line-type features based on point-sampled geometry. This method employs principal component analysis and minimum spanning graph to detect boundary edges. Although those approaches were successful in surface reconstruction of small objects, they are not suitable for large-scale objects such as precast concrete elements due to the prohibitive computational costs of running complex algorithms. In this study, a new and robust edge detection algorithm is developed for dimensional QA of precast concrete elements, and it is described in Chapter 2.3.3.

2.2.3 Object recognition and classification based on point cloud data

Object recognition and classification from point cloud data have gained much interest in the computer vision community due to its various applications such as urban modelling, simultaneous localization and mapping. In object recognition, researchers have extracted various features from point cloud data. Althaus and Christensen (2003) used line features to detect corridors and doorways. Hahnel et al. (2003) employed a region growing technique to identify planes. For object classification, Golovinskiy et al. (2009) proposed a method based on graph cut algorithm to classify various objects such as cars and trees from airborne point clouds. Triebel et al. (2006) classified the building components using associative Markov networks. The aforementioned studies, however, are mostly based on supervised learning, which requires expensive computations and sufficient training data for accurate object recognition and classification. Tang et al. (2009) proposed a range image based object detection technique, which is most relevant to our object detection study. Although Tang et al. (2009) directly detects objects with the help of range images generated from point cloud data, the detection is not automated because three points on the range image need to be manually selected to detect the pose of a target object plane. In this study, the object detection process is automated for the dimensional measurement of precast concrete elements.

2.2.4 Laser scanning-based quality inspection of concrete structures

For the QA of concrete structures based on laser scanning, Akinci et al. (2006) proposed a general framework which compares the as-built model of a structure generated from a laser scanner with its design CAD model. However, these require much manual work in the generation of an as-built model. Bosche (2010) proposed an automated technique of recognizing 3D CAD objects from laser-scanned data for dimensional compliance inspection of construction elements. Other laser
scanning-based QA studies for concrete structures have mainly focused on detection of damages such as large cracks, flatness and spallings (Teza et al. 2009; Tang et al. 2011; Olsen et al. 2010; Liu et al. 2010). Little work has been done on dimensional estimation of construction components, and there have been no studies on dimensional QA of precast concrete panels. Hence, there is an urgent need for developing an accurate and automated dimensional QA technique for precast concrete panels.

2.3 Development of an Automated Dimensional Quality Assessment Technique

This study aims to develop an automated dimensional QA technique for precast concrete panels. Fig. 2.2 (a) illustrates the schematic of the overall hardware configuration for the proposed dimensional QA technique. For the purpose of this study, it is assumed that the precast concrete panel has a rectangular planar surface and a laser scanner positioned above the panel scans the whole surface of the panel in a single scan. Fig. 2.2 (b) shows the necessary steps for the proposed dimensional QA, including data acquisition, data pre-processing, edge and corner extraction, compensation for edge loss, and dimension estimation and QA. The details for each step are described below.

![Figure 2.2](image)

**Figure 2.2** The proposed precast concrete dimensional QA technique: (a) Schematic of overall system configuration; (b) Dimensional QA procedures
2.3.1 Data acquisition

It is necessary to first determine the position and scan parameters of the laser scanner to achieve the highest inspection quality. There are three main factors which influence the measurement accuracy of a laser scanner: 1) distance; 2) the incident angle between a laser scanner and a target structure; and 3) angular resolution of a laser scanner. The effects of these parameters on dimension estimation accuracy are investigated in Chapter 2.4. Once the position and scan parameters of the laser scanner are determined, a region of interest (ROI) covering the precast concrete element is selected after a coarse scan. It is desirable to make the ROI slightly bigger than the target area to reduce the scan time and accelerate the post-processing of data. Then, a fine scan is conducted over the ROI, generating a point cloud containing a set of 3D points, i.e., \((x_i, y_i, z_i)\), \(i = 1, ..., N\), where \(N\) is the number of total scan points. Note that the scanning and data acquisition are conducted automatically without human intervention once the scan parameters of the laser scanner and ROI are manually determined prior to data acquisition. The word ‘fully automated’ used in this study implies that once the raw scan data becomes available, the proposed technique operates in a fully automated manner for all data processing from data-preprocessing to quality assessment.

2.3.2 Data pre-processing

2.3.2.1 Coordinate transformation of a point cloud

![Coordinate transformation from a laser scanner to the target object: (a) Laser scanner coordinate system; (b) Object coordinate system](image)

**Figure 2.3** Coordinate transformation from a laser scanner to the target object: (a) Laser scanner coordinate system; (b) Object coordinate system
Chapter 2. Quality Assessment Technique I: Dimensional Estimation

Figure 2.4 Autonomous determination of three corner points of the target object from a range image: (a) The initial range image of a target specimen; (b) Edge and corner detection in the binary image using the Canny edge detector and the Hough transform; (c) Determination of three points near the corner of the target object.

<table>
<thead>
<tr>
<th>Input:</th>
<th>scan points (S.Point), range image, three corners (C1, C2, C3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output:</td>
<td>three pixel points near corners (Bestp1, Bestp2, Bestp3)</td>
</tr>
</tbody>
</table>

Initialization

1. minValue = +\infty;
2. Bestp1 = Bestp2 = Bestp3 = 0;

Iterative Search

3. for all \( p1 \) satisfies \( |p1 - C1| \leq \epsilon \) and \( \text{range}(p1) \leq \alpha \)
4. for all \( p2 \) satisfies \( |p2 - C2| \leq \epsilon \) and \( \text{range}(p2) \leq \alpha \)
5. for all \( p3 \) satisfies \( |p3 - C3| \leq \epsilon \) and \( \text{range}(p3) \leq \alpha \)
6. \( \bar{p}1\bar{p}2 = S.Point(p2) - S.Point(p1); \)
7. \( \bar{p}2\bar{p}3 = S.Point(p3) - S.Point(p2); \)
8. \( \text{Angle} = \cos^{-1} \left( \frac{\bar{p}1\bar{p}2 \cdot \bar{p}2\bar{p}3}{|\bar{p}1\bar{p}2| \cdot |\bar{p}2\bar{p}3|} \right); \)
9. if \( |90 - \text{Angle}| < \text{minValue} \)
10. \( \text{minValue} = |90 - \text{Angle}|; \)
11. \( \text{Bestp1} = p1; \text{Bestp2} = p2; \text{Bestp3} = p3; \)
12. end
13. end
14. end
15. end

Figure 2.5 Three pixel point selection algorithm for the automated coordinate transformation

Once the point cloud is acquired, the 3D coordinates with respect to the laser scanner (Fig. 2.3 (a)) are transformed into a new coordinate system with respect to one of the corners of the panel such that the surface of the panel is nearly parallel to the new x-y plane as shown in Fig. 2.3 (b). The main objective of the coordinate transformation is to remove unwanted background scan points behind the target so that only the scan points on the target surface are retained for next data processing.
For coordinate transformation, three points near the corners of the precast concrete element are first identified from the range image as shown in Fig. 2.4. Here, the range image is a 2D image generated from the acquired point cloud, and each pixel point within a range image is coupled with the corresponding scan point in point cloud data so that each pixel point of the range image holds the distance value from the laser scanner to the corresponding scan point. In Fig. 2.4 (a), the target object closer to the laser scanner is shown in a darker grey while the background behind the object is shown in a lighter grey. In Fig. 2.4 (b), the Canny edge detection (Canny 1986) is first conducted on the range image to obtain an edge (binary) image. Note that the edge points extracted by the Canny edge detector are used only for coordinate transformation, but not for subsequent dimensional estimations due to the mixed-pixel problem at edges, as would be discussed in Chapter 2.3.4. The Hough transform (Ballard 1981) is then employed to obtain the edge lines of the target object from the edge image. Here, there is a constraint for the edge line extraction that the lengths of edge lines should be longer than a certain threshold so that only the edges of the panel are extracted. Next, the four intersection points between the obtained edge lines are identified as the corner points of the object. Subsequently, the proposed algorithm, as shown in Fig. 2.5, determines the three pixel points used for the coordinate transformation. First, candidate pixel points surrounding each corner point (C1, C2, and C3) are limited to 1) ones from each corner point within a certain margin bound (ε) and 2) with a range distance of less than a range threshold (α). Note that ε and α are selected as 10 pixels and the mean range value of the range image in this study such that only pixel points, which are on the target object surface and 10-pixel distance from each corner point, are selected as the candidate pixel points. Iterative searching for finding best pixel points is then performed based on the condition that the horizontal and vertical lines formed by the three scan points corresponding to the selected three pixel points are orthogonal in the 3D space. Note that the orthogonality between the horizontal and vertical lines should be preserved to avoid distortion of the scan points after coordinate transformation. However, since a perfect right angle between the two lines might not be guaranteed due to limited spatial resolution of laser scanners, three pixel points forming the closest angle to right angle are determined in this study. Once the three points are chosen, a plane of the precast concrete panel is determined and all 3D points in the point cloud are then transformed into the object coordinate system as shown in Fig. 2.3 (b).
2.3.2.2 Removal of unnecessary scan points and projection to a 2D plane

![Margins](image)

**Figure 2.6** Elimination of unnecessary scan points and dimensional reduction: (a) Removal of scan points outside the target object with margins; (b) Dimensional reduction through projection of the filtered points onto a fitted plane.

To avoid the difficulties associated with redundant data, two data pre-processing tasks are conducted in this step. Once the coordinates of the scan points are aligned along the local x and y axes of the object, unnecessary scan points are eliminated as shown in Fig. 2.6 (a). Note that the size of the rectangular margin box in each direction is determined to be ‘design length ± margin’ with the following assumptions: 1) The dimensions of an ideal precast concrete panel are known from a blueprint, and 2) The deviation of the dimensions of an actual precast concrete panel from the design values is within a certain margin. The nominal margin was selected to be 2 cm since the margin is large enough compared to the maximum distance error (2 mm) produced by the laser scanner used in this study. Then, the surface plane of the precast concrete panel is estimated by least-squares fitting the retained scan points inside the margins. Finally, the filtered scan points are projected from the 3D space onto the fitted 2D plane as shown in Fig. 2.6 (b).
2.3.3 Edge and corner extraction

The proper extraction of the edges and corner points of the target object is crucial to precisely estimate the dimensions of the precast concrete panel. Here, an automated algorithm named as ‘Vector-sum algorithm’ is developed to extract the scan points along the horizontal and vertical edge lines of the precast concrete element.

Figs. 2.7 and 2.8 show the principle of the ‘vector-sum’ algorithm for the scan points inside and on the edge of the target object, respectively. To simplify the description of the algorithm, it is assumed that all scanned points are equally spaced in both horizontal and vertical directions as shown in Fig. 2.7 (a). In practice, the equal scan spacing is not a necessary condition. Once one scan point is designated as a reference point, \( p_n \), the eight nearest neighboring points around the reference point denoted as \( p_n^m, m = 1, 2, \ldots, 8 \), are selected based on the Euclidean distance. Next, the eight vectors, \( p_n^m, \) connecting the reference point to each neighboring points are computed as shown in Fig. 2.7 (b). Finally, the summation of the eight vectors, \( V(p_n) \), is computed as follows.

![Figure 2.7](image-url)

**Figure 2.7** Vector-sum algorithm for a scan (reference) point inside the target object: (a) Determination of eight nearest neighboring points around the reference point; (b) Vector representation from the reference point to each the eight nearest neighboring points; (c) Vector-sum of the eight vectors (the magnitude of vector-sum is zero).
Figure 2.8 Vector-sum algorithm for a scan (reference) point along the edge of the target object: (a) Determination of eight nearest neighboring points around the reference point; (b) Vector representation from the reference point to each of the eight nearest neighboring points; (c) Vector-sum of the eight vectors (the magnitude of vector sum is 5 times of the spacing interval).

\[ V(p_n) = \sum_{m=1}^{8} p_n p_m \]  \hspace{1cm} (2.1)

When the reference point, \( p_n \), lies inside the region of the panel, \( V(p_n) \) becomes zero as shown in Fig. 2.7 (c). On the other hand, if \( p_n \) rests on the edge of the panel as shown in Fig. 2.8 (c), \( V(p_n) \) becomes 5 times of the point-to-point spacing interval (S). Based on this observation, the magnitude of \( V(p_n) \) serves as an indicator that classifies whether a reference point is an edge point or not. To formalize this classification, a threshold value of 2.5 times the scanning spacing is used as follows.

\[ \text{If } V(p_n) > 2.5S, \text{ } p_n \text{ is a potential edge point. Otherwise, } p_n \text{ is inside the panel region} \]

Note that \( S \) varies with respect to scan parameters such as scan distance, incident angle and angular resolution. In reality, the vector-sum algorithm can misclassify non-edge points as edge points mainly
due to the measurement error of laser scanners. In this study, the algorithm is further developed to eliminate false edge points. The development of the non-edge point removal algorithm is based on the observation that the non-edge points are sparsely scattered from the edges while the edge points are densely aligned along the edge with equal spacing (see Fig. 2.9). From this observation, a classifier for removal of false edge points is proposed. The filtering is performed only on the candidate edge points identified from the previous Vector-Sum algorithm. For a candidate edge point, \( p_n \), the distance from \( p_n \) and to the 8th nearest point \( p_{n8} \) should be 4 times of \( S \) if \( p_n \) is an edge point as shown in Fig. 2.9 (b). On the other hand, the distance \( p_{n8} \) would be longer than 4\( S \) if \( p_n \) is a non-edge point. To be conservative, a threshold for the filtering is set to be 6\( S \),

\[
\text{If } p_{n8} < 6S, \text{ then } p_n \text{ is an edge point. Otherwise, } p_n \text{ is a non-edge point.}
\]

Figure 2.9 Removal of non-edge points from edge candidate points: (a) A set of edge candidate points identified by the Vector-sum algorithm; (b) If the reference point is indeed on the edge of the target object, the distance from the reference point to the 8th closest neighboring point should be about four times of the spacing interval; (c) For a non-edge reference point, the neighboring points are sparsely scattered and the distance from the reference point to the 8th closest point would be much longer.
2.3.4 Compensation for edge dimension loss

![Diagram of surface and laser beam with mixed-pixels](image)

**Figure 2.10** Mixed-pixel phenomenon: (a) The mixed-pixel phenomenon typically occurs at the boundaries of an object where the laser beam is split into two and reflected from two discontinuous surfaces; (b) An example of mixed-pixels from laser scanning data.

![Diagram of dimensional loss compensation model](image)

**Figure 2.11** Dimensional loss compensation model (Tang et al. 2009)

Although a laser scanner provides reliable spatial information of an object in most occasions, a certain adverse scanning configuration between the laser scanner and the object can adversely affect measurement accuracy. One such condition is known as the mixed-pixel effect (Hebert and Krotkov 1991; Mills and Barber 2004; Lichti et al. 2005; Tang et al. 2007). The mixed-pixel phenomenon occurs when the laser beam is split into two and reaches two distinctive surfaces which have different distances from the laser scanner as shown in Fig. 2.10 (a). Under this situation, the encoder of the laser scanner receives a mixture of two signals reflected separately from the two surfaces resulting in
inaccurate range measurements for the scanned point. Fig. 2.10 (b) shows an example of the mixed-pixel phenomenon obtained from the test specimen investigated in this study. It can be seen that a number of scanned points on the edge lines deviate and appear apart from the actual edge lines due to the mixed-pixel phenomenon. Although recently introduced full-waveform LiDAR may reduce range measurement error in boundaries, it cannot entirely remove the mixed pixel problem (Godbaz et al. 2008).

To cope with the mixed-pixel phenomenon, an edge loss compensation model (Tang et al. 2009), which quantitatively estimates dimension loss on the edges caused by the mixed-pixels, is employed to compensate for the dimensional loss of the precast concrete panel as shown in Fig. 2.11. For the phase-shift laser scanner used in this study, the lower and the upper bounds, \( E_{\text{lower}} \) and \( E_{\text{upper}} \), of the dimensional loss due to the mixed pixel phenomenon can be expressed as:

\[
E_{\text{lower}} = \frac{D}{2} = \frac{D_0 + \text{abs}(L - L_0) \cdot \alpha_d + \omega \cdot t_s \cdot L}{2 \cdot \cos(\alpha_i)} \\

E_{\text{upper}} = S + \frac{D}{2} = \frac{L \cdot \alpha_x}{\cos(\alpha_i)} + \frac{D_0 + \text{abs}(L - L_0) \cdot \alpha_p + \omega \cdot t_s \cdot L}{2 \cdot \cos(\alpha_i)}
\]

(2.2)

where \( D_0 \) and \( D \) are the laser beam diameters of a laser scanner at the focal point \((L_0)\) and at the object surface, respectively. \( L \) denotes the scan distance between the object and the laser scanner. \( \omega \) is the laser scanner’s vertical rotation rate (speed) in radians/second and \( t_s \) is the laser scanner’s sampling time in seconds. Note that the effect of the horizontal rotation rate of the laser scanner on the dimensional loss compensation model is neglected since the horizontal rotation rate of the laser scanner is much lower than the vertical rotating rate (typically 1/2000 times lower). \( \alpha_d, \alpha_t \) and \( \alpha_r \) are the divergence rate of the laser beam, the scanner’s incident angle and angular resolution, respectively. In this study, the dimensional loss, which needs to be compensated for, is assumed to be the average of the lower and the upper bounds of the dimensional loss because the edge loss is assumed uniformly distributed across the theoretical range:

\[
E_{\text{comp}} = \frac{E_{\text{lower}} + E_{\text{upper}}}{2} = \frac{(D_0 + \text{abs}(L - L_0) \cdot \alpha_p + \omega \cdot t_s \cdot L + L \cdot \alpha_r)}{2 \cdot \cos(\alpha_i)}
\]

(2.3)
2.3.5 Dimension estimation & quality assessment

In this step, three dimensional properties are computed using the previously estimated initial dimensions \( M \) and the estimated dimensional loss value \( E_{\text{comp}} \): (1) the dimensions (length and width) of the precast concrete panel, (2) the dimension and position of the shear pockets (rectangular holes within the precast concrete panels), (3) the squareness of the precast concrete panel. For each object (either the panel or the inner rectangular hole), the length is defined as the distance (length) of the horizontal edge line, and the width as the distance (length) of the vertical line. The position of a shear pocket is defined as the distance from the center of the shear pocket to the closest horizontal and vertical edges of the precast concrete panel. Also, the squareness error is defined as the length difference between the longer sides of a precast component (PCI 2000). The squareness error in this study is the length difference between the upper and the lower horizontal lines. Table 1 shows the estimated dimension taking account of the dimensional edge loss. Note that for the dimension estimation of the precast concrete panel, \( 2 \cdot E_{\text{comp}} \) is added to the initially estimated dimension \( M \) because dimension losses occur at the two edges, e.g., left and right vertical edges for horizontal dimension estimation. On the other hand, for the dimension estimation of a shear pocket, \( 2 \cdot E_{\text{comp}} \) is subtracted from the initial estimation because the edge points lie outside the boundary of the shear pocket. For the position estimations of a shear pocket, only one dimension loss \( E_{\text{comp}} \) is added to the initial estimation since the center of the shear pocket can be calculated based only on the previously extracted corner points of the shear pocket. For the squareness estimations, no dimension loss compensation is needed since it is also estimated based only on the previously extracted corners of the precast concrete panel. Once the dimensional estimation is completed, the estimated dimensions are finally compared with the design specifications for quality assessment.

<table>
<thead>
<tr>
<th>Dimensional property</th>
<th>Estimated dimension</th>
</tr>
</thead>
<tbody>
<tr>
<td>Length and width of precast concrete panel</td>
<td>( M + 2 \cdot E_{\text{comp}} )</td>
</tr>
<tr>
<td>Length and width of shear pocket</td>
<td>( M - 2 \cdot E_{\text{comp}} )</td>
</tr>
<tr>
<td>Position of shear pocket</td>
<td>( M + E_{\text{comp}} )</td>
</tr>
<tr>
<td>Squareness of precast concrete panel</td>
<td>( M )</td>
</tr>
</tbody>
</table>

* \( M \) is the initially calculated dimension

Table 2.1 Dimension estimation formula with dimensional compensation
2.4 Dimensional Assessment Test of a Laboratory Specimen

2.4.1 Description of test and laboratory specimen

![Laboratory test configuration and specimen](image)

**Figure 2.12** Laboratory test configuration and specimen: (a) Test set-up; (b) Dimensions of the laboratory test specimen

**Table 2.2** Experiment scenario - laser scanning parameters

<table>
<thead>
<tr>
<th>Scan parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>External Distance</td>
<td>4 m, 8 m, 12 m, 16 m</td>
</tr>
<tr>
<td>Incident angle</td>
<td>0°, 15°, 30°, 45°</td>
</tr>
<tr>
<td>Internal Angular resolution</td>
<td>0.009°, 0.018°, 0.036°</td>
</tr>
<tr>
<td>Laser beam size</td>
<td>Diameter 3.8 mm at 0 m with divergence angle 0.16 milliradians</td>
</tr>
<tr>
<td>Vertical rotation speed</td>
<td>Maximum 5820 rounds/min</td>
</tr>
<tr>
<td>Measurement rate</td>
<td>976,000 points/sec @0.009° angular resolution; 488,000 points/sec @0.018°; 244,000 points/sec @0.036°</td>
</tr>
</tbody>
</table>

A laboratory experiment was conducted to validate the proposed dimensional quality assessment technique. The goals of this laboratory test were to estimate 1) the dimensions of three objects (the panel itself and two rectangular holes in it), 2) the positions of the holes with respect to the panel, and 3) the squareness of the panel.

In this experiment, a set of point cloud data was acquired from the test specimen using a phase-shift laser scanner, FARO Focus-3D (FARO 2014), shown in Fig. 2.12 (a). The phase-shift laser
scanner was selected with the target scanning distance (less than 20 m) and target dimension estimation tolerance (less than 6 mm) taken into account. The scanner offers distance accuracy of ± 2 mm in a range of 0.6 m and 120 m, and a measurement rate of up to 976,000 points/sec. The scanner was set up and leveled on a tripod at 1.5 m height, which was at the same height as the center of the test specimen. Instead of an actual concrete panel, a rectangular test specimen made of Styrofoam with a size of 910 mm × 610 mm was used as shown in Fig. 2.12 (b). Two identical through-thickness rectangular holes with dimensions of 250 mm × 150 mm were introduced to emulate shear pockets, which were needed to connect precast concrete panels with bridge girders. PCI manual states that the length and width of precast concrete panels and shear pockets as well as the position of shear pockets should be carefully inspected with dimensional tolerance of ± 6 mm (PCI, 2000).

The laboratory test was performed by varying the following three parameters to investigate their effects on the accuracy of the proposed technique: 1) scan distance between the laser scanner and the test specimen, 2) angular resolution of the laser scanner, and 3) incident angle between the laser beam and the test specimen. Table 2.2 shows the details of the investigated scan parameters. A total of 48 scans with different scan parameters were conducted: four different distances (4, 8, 12, 16 m), four different incident angles (0, 15, 30, 45°), and three varying angular resolutions (0.009, 0.018, 0.036°). The scan distance and incident angle were selected based on an assumption that the length of a precast concrete panel would not exceed 30 m. These two parameters are called external parameters since the laser scanner needs to be repositioned for each scan. The angular resolution was the only controllable internal parameter of the laser scanner, and the other internal parameters such as rotation speed and measurement rate were automatically selected based on the angular resolution. For instance, when the angular resolution was chosen to be 0.009°, the vertical rotation speed and the measurement rate of the scanner were set as 5,820 rounds/min and 976,000 points/sec, respectively.

2.4.2 Laboratory experiment results

Fig. 2.13 shows the edge and corner points extraction results obtained from the laboratory specimen by setting the scan distance, incident angle and angular resolution to 8 m, 0° and 0.009°, respectively. The 3D scan points were first projected onto a fitted plane obtained from least square minimization method (Fig. 2.13 (a)). Then, the vector-sum algorithm in Eq. (2.2) was applied to the projected scan points to extract edge points (Fig. 2.13 (b)). Using the filtering described in Chapter 2.2.3, false edge (non-edge) points were removed (Fig. 2.13 (c)). Finally, the corner points of the target objects are identified as the intersections of the lines fitted from the edge points (Fig. 2.13 (d)).
Figure 2.13 Edge and corner points extraction results (scanning parameters of 8 m scan distance, 0° incident angle, and 0.009° angular resolution): (a) Scan points projected onto a fitted plane; (b) Edge points extraction using the Vector-sum algorithm; (c) Removal of the non-edge points; (d) Corner detection.

Table 2.3 shows the performance of the proposed dimension estimation technique and how its accuracy varies depending on scan parameters. The dimension error is defined as the difference between the design dimension and the one estimated by the proposed technique. In this laboratory test, 4 dimension errors (2 lengths and 2 widths) were estimated for each object such that a total of 12 dimension errors (3 objects × 4 dimensions) were obtained from each scan. Note that the dimension error presented in Table 3 is the average of these 12 dimension errors. The dimension estimation error was 3.06 mm on average for 48 scans. 526 times out of 576 estimated dimensions (48 scans and 12 dimensions for each scan) were within the target tolerance (± 6 mm), resulting in 91.3 % of satisfactory dimension estimation. It is observed that the incident angle is the main parameter that affects the accuracy of the dimension estimation. In particular, the 45° incident angle seriously deteriorated the dimension error such that the average error was 4.3 mm and 60.0 % of the over-tolerance dimensions was obtained from the 45° incident angle cases. On the other hand, the scan distance and angular resolutions had a negligible impact on the dimension estimation accuracy.
### Table 2.3 Average dimension estimation error of the three target objects, the panel and two rectangular holes, with varying scan parameters

<table>
<thead>
<tr>
<th>Incident angle (°)</th>
<th>Distance = 4 m</th>
<th>Incident angle (°)</th>
<th>Distance = 8 m</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Angular resolution(°)</td>
<td></td>
<td>Angular resolution(°)</td>
</tr>
<tr>
<td></td>
<td>0.009 0.018 0.036</td>
<td></td>
<td>0.009 0.018 0.036</td>
</tr>
<tr>
<td>0</td>
<td>2.8 2.8 2.1</td>
<td>0</td>
<td>2.5 2.5 1.7</td>
</tr>
<tr>
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<td>3.0 1.7 2.0</td>
<td>15</td>
<td>2.1 1.7 1.7</td>
</tr>
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<td>30</td>
<td>1.5 2.2 2.7</td>
</tr>
<tr>
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<td>8.4 4.3 2.2</td>
<td>45</td>
<td>4.4 2.7 4.8</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Incident angle (°)</th>
<th>Distance = 12 m</th>
<th>Incident angle (°)</th>
<th>Distance = 16 m</th>
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<td>Angular resolution(°)</td>
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<td>Angular resolution(°)</td>
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<td></td>
<td>0.009 0.018 0.036</td>
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<td>2.0 2.0 3.7</td>
<td>0</td>
<td>2.0 2.4 5.2</td>
</tr>
<tr>
<td>15</td>
<td>1.9 2.5 2.8</td>
<td>15</td>
<td>2.2 2.5 5.2</td>
</tr>
<tr>
<td>30</td>
<td>2.0 2.5 4.0</td>
<td>30</td>
<td>2.2 2.4 7.2</td>
</tr>
<tr>
<td>45</td>
<td>4.1 2.2 4.9</td>
<td>45</td>
<td>4.8 2.5 6.6</td>
</tr>
</tbody>
</table>

### Table 2.4 Average position estimation error of the two rectangular holes with varying scan parameters

<table>
<thead>
<tr>
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<th>Distance = 4 m</th>
<th>Incident angle (°)</th>
<th>Distance = 8 m</th>
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<tbody>
<tr>
<td></td>
<td>Angular resolution(°)</td>
<td></td>
<td>Angular resolution(°)</td>
</tr>
<tr>
<td></td>
<td>0.009 0.018 0.036</td>
<td></td>
<td>0.009 0.018 0.036</td>
</tr>
<tr>
<td>0</td>
<td>2.3 2.3 3.9</td>
<td>0</td>
<td>1.3 2.5 2.0</td>
</tr>
<tr>
<td>15</td>
<td>2.3 1.8 1.0</td>
<td>15</td>
<td>2.8 2.2 2.3</td>
</tr>
<tr>
<td>30</td>
<td>2.1 2.1 2.2</td>
<td>30</td>
<td>2.3 3.9 3.0</td>
</tr>
<tr>
<td>45</td>
<td>9.6 6.2 5.3</td>
<td>45</td>
<td>8.1 4.1 5.0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Incident angle (°)</th>
<th>Distance = 12 m</th>
<th>Incident angle (°)</th>
<th>Distance = 16 m</th>
</tr>
</thead>
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<td></td>
<td>Angular resolution(°)</td>
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<td></td>
<td>0.009 0.018 0.036</td>
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</tr>
<tr>
<td>0</td>
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<td>0</td>
<td>1.9 2.3 1.1</td>
</tr>
<tr>
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<td>2.1 3.5 1.0</td>
<td>15</td>
<td>2.7 3.9 8.2</td>
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<td>2.4 3.6 8.4</td>
<td>30</td>
<td>1.9 3.6 12.4</td>
</tr>
<tr>
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<td>6.2 5.9 8.1</td>
<td>45</td>
<td>7.0 4.2 13.6</td>
</tr>
</tbody>
</table>
Table 2.5 Squareness estimation error of the panel with varying scan parameters

<table>
<thead>
<tr>
<th>Incident angle (°)</th>
<th>Distance = 4 m Angular resolution(°)</th>
<th>Distance = 8 m Angular resolution(°)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.009 0.018 0.036</td>
<td>0.009 0.018 0.036</td>
</tr>
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<td>0.3 0.0 0.4</td>
<td>0.2 0.6 1.7</td>
</tr>
<tr>
<td>15</td>
<td>0.1 0.5 0.6</td>
<td>0.5 0.5 0.9</td>
</tr>
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<td>30</td>
<td>0.3 0.2 0.1</td>
<td>0.3 1.1 0.9</td>
</tr>
<tr>
<td>45</td>
<td>3.1 0.5 1.8</td>
<td>0.6 0.0 1.0</td>
</tr>
<tr>
<td>Incident angle (°)</td>
<td>Distance = 12 m Angular resolution(°)</td>
<td>Distance = 16 m Angular resolution(°)</td>
</tr>
<tr>
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<td>0.009 0.018 0.036</td>
<td>0.009 0.018 0.036</td>
</tr>
<tr>
<td>0</td>
<td>0.2 1.7 0.7</td>
<td>2.5 0.4 11.7</td>
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<tr>
<td>15</td>
<td>1.1 0.7 2.6</td>
<td>0.9 1.9 1.0</td>
</tr>
<tr>
<td>30</td>
<td>0.4 2.2 7.8</td>
<td>0.3 0.2 7.2</td>
</tr>
<tr>
<td>45</td>
<td>3.3 3.6 4.6</td>
<td>1.0 5.1 7.3</td>
</tr>
</tbody>
</table>

Table 2.4 presents the position errors of the two rectangular holes estimated by the proposed technique under varying scan parameters. Here, the distance between the center point of each object and the nearest edge of the panel is defined as the position as mentioned earlier. The position error of each hole was calculated in both horizontal and vertical directions so that a total of 4 position errors (2 objects × 2 positions) were obtained from each scan. Note that the position error presented Table 4 is the average of these 4 position errors. The position estimation error was overall 4.09 mm for 192 dimension estimations (48 scans and 4 positions for each scan), and 154 dimensions out of 192 were successfully estimated within the tolerance. Like the dimension error results in Table 2.3, the estimation performance deteriorated with increasing incident angles, particularly in 45° incident angle cases where the average position error was 6.9 mm and 52.6 % of the over-tolerance dimensions was obtained.

Table 2.5 shows the squareness estimation error for the panel. The average squareness error was 1.76 mm, and squareness was successfully estimated for 44 cases out of 48 scans (48 scans and 1 squareness estimation for each scan), resulting in a success rate of 91.7%. The success rate for the squareness estimation was higher than the dimension and position estimations because it was estimated based on only the extracted corner information without any edge loss compensation.
Figure 2.14 Effects of scan parameters on dimension and position estimations: (a), (b) and (c) investigate effects of distance, incident angle and angular resolution on dimensions of three targets, respectively. (d), (e) and (f) investigate effects of distance, incident angle and angular resolution on positions of two rectangular holes, respectively.

In Fig. 2.14 (a), (b) and (c), the effects of the scan parameters on the length and width estimations of the three targets are investigated. To examine the effect of each scan parameter individually, only one scan parameter was varied in each subfigure while the other two parameters were fixed to their reference values, i.e., distance: 8 m, incident angle: 0° and angular resolution: 0.009°. In addition, error bars are used to show error bounds for the dimensional measurements. The width of the error bar was two times the standard deviation of each measurement. As expected, the
dimension estimation is not much influenced by the scan distance. The incident angle effect, there was no big difference in the dimension errors among incident angles of 0°, 15° and 30°. However, in the case of 45°, the dimension error (4.4 mm) became much larger than the other dimension errors (2.5, 2.1 and 1.5 mm) of lower incident angles. This incident angle effect agrees with past work on measurement error of the laser scanner by other researchers (Laefer et al. 2009; Lichti 2007). The angular resolution, however, showed no significant trend with the increase in angular resolution. As shown in Fig. 2.14 (d), (e) and (f), similar parameter studies were conducted for the estimation of the horizontal and vertical positions of two rectangular holes. From the results, the incident angle parameter is more dominant than scan distance and angular resolution parameters in a similar manner to the dimension results. In the case of the 45° incident angle, the position error (8.1 mm) is the highest among those (1.3, 2.8 and 2.3 mm) of the other incident angle cases. From the results, scans under incident angles of less than 45° are recommended for dimensional quality assessment of precast concrete panels. The cause of these observations is illustrated in the following paragraph.

Figure 2.15 Edge point extraction results with a large incident angle: (a) With scan parameters (distance 8 m, incident angle 0° and angular resolution 0.018°); (b) With incident angle of 45°.
Fig. 2.15 illustrates how the edge detection using the vector-sum algorithm is affected by the incident angle and angular resolution. A comparison of Figs. 2.15 (a) and (b) shows that the number of the false edge points increase with the increasing incident angle. The increase in the false edge points can be attributed to the reason as shown in Fig. 2.16 (a): 1) As the incident angle increases, the size of the incident laser beam on a target increases along the axis of the incident angle, and the shape of the laser beam becomes elliptical; 2) The scan spacing becomes larger as the incident angle increases. Due to these problems, the alignment of the scan points on the surface of the target become irregular, going against the assumption of the vector-sum algorithm and causing the edge point detection performance to deteriorate. In addition, a large incident angle may cause the side scan points to affect the dimensional estimation. Fig. 2.16 (b) shows an example of side scan points with 8 m scan distance, 0.018° angular resolution and 45° incident angle. The right side of the two shear pockets (inside objects) contains the scan points of the side regions, which may lead to incorrect dimension estimation. In order to prevent this, increasing the scan distance (decreasing incident angle) is recommended for real applications of the proposed technique.

Figure 2.16 Scanning with increasing incident angle: (a) Distortion of the beam spot from a circle to an ellipse shape and increase of the scan spacing are occurred as incident angle increases; (b) The right side of the two shear pockets contains the scan points of the side regions of the objects.
The angular resolution in a short scan distance can also affect dimensional estimation results. Tables 2.3-5 show that high scan densities (a short scan distance and dense angular resolution) can produce larger estimation errors than low scan densities. For example, given the identical scan distance of 4 m and incident angle of 45°, the dimensional error was larger with a 0.009° angular resolution (8.2 mm) than with a 0.036° angular resolution (2.2 mm) Fig. 2.17 shows the effect of angular resolution on edge point extraction results when the scan parameters are set at scan distance of 4 m and an incident angle of 0°. It can be seen that the edge detection performance deteriorates with increasing angular resolution. This deterioration can be explained by the fact that, as the angular resolution increases, the spacing between two adjacent scan points (0.673 mm = distance × angular resolution ÷ cos(incident angle)) becomes irregular because the spacing gets closer to the measurement noise level (0.6 mm at 90% reflectivity) of the laser scanner used in this study. To prevent this problem, the scan distance and angular resolution should be chosen properly so the point-to-point distance is larger than the laser scanner’s measurement noise levels.

Figure 2.17 The effect of angular resolution on edge point extraction (at 4 m distance and with 15° incident angle): (a) 0.009° angular resolution, and (b) 0.036° angular resolution
2.5 Application to Actual Precast Concrete Panel

2.5.1 Test configuration

To further examine the effectiveness of the proposed dimensional quality assessment technique, tests on two actual precast concrete panels were conducted. The overall experimental configuration and the investigated precast concrete panels are shown in Fig. 2.18. The bottom surface of the precast concrete panels was fixed onto a concrete wall and scanned by the laser scanner as shown in Fig. 2.18 (a). In this experiment, the laser scanner was positioned 10m from the precast concrete panels and 2.5 m from the ground, resulting in a maximum incident angle of 5.7°. Scans with three different angular resolution cases (0.009, 0.018 and 0.036°) were performed. Fig. 2.18 (b) describes the two precast concrete panels tested in the experiments. Precast concrete panel I was assumed a normal (well-manufactured) panel and precast concrete panel II was fabricated to represent an abnormal panel with dimensional errors exceeding the tolerance. For both panels, there are six rectangular shear pockets with identical dimensions of 250 mm × 150 mm. For precast concrete panel II, three dimensional errors were intentionally introduced: 1) 20 mm loss of the upper horizontal dimension (1980 mm) 2) position shift of No. 2 shear pocket to the right and downward by both 25 mm 3) position shift of No. 6 shear pocket to the left and downward by both 25 mm.
2.5.2 Experimental results

**Figure 2.19** Edge and corner extraction results on: (a) Precast concrete panel I; (b) Precast concrete panel II (obtained with angular resolution of 0.009°)

Fig. 2.19 shows the result of the edge and corner point extractions for two the precast concrete panels. The edge and corner points of the precast panels and the six shear pockets for each panel were successfully obtained from the vector-sum algorithm. Tables 2.6, 2.7 and 2.8 summarize the dimensional estimation results compared to the design dimensions of the precast concrete panels. For the dimension estimation in Table 2.6, the dimension error was an average of 1.9 mm for 84 dimension estimations (6 scans and 14 dimensions for each scan) producing a success rate of 95.2 % within the tolerance. Note that the vertical dimension estimation is more influenced by the angular resolution than the horizontal one. For the position estimation in Table 2.7, the average position estimation error of the shear pockets was 1.8 mm with a success rate of 96.5 %. For the squareness error in Table 2.8, the average squareness error was 2.7 mm and all cases were within the tolerance. In order to compare the estimated results with the conventional method, manual inspections were conducted on the two precast concrete panels. Table 2.9 shows the manual inspection error results
compared to the design dimensions of the precast panels. The average errors of the dimension and position of the two precast panels were 0.5 and 1.9 mm, respectively, which have differences of 1.4 and 0.1 mm compared to the estimation result of the proposed technique. This demonstrates that the proposed dimensional quality assessment technique can accurately and reliably measure the length, position and squareness of the precast concrete panels.

| Table 2.6 Dimension estimation error of precast concrete panels I & II and their six shear pockets. |
|---|---|---|---|---|---|---|
| Precast Slab | Precast Slab I | Precast Slab II |
| Angular resolution (°) | 0.009 | 0.018 | 0.036 | 0.009 | 0.018 | 0.036 |
| Slab | | | | | | |
| Hori. Upper | 1.4 | 0.6 | 0.3 | 1.1 | 0.5 | 2.9 |
| Hori. Bot. | 1.3 | 0.4 | 0.7 | 2.4 | 4 | 2.6 |
| Vert. | 0.9 | 0.1 | 1.2 | 4.1 | 1.4 | 3.8 |
| S. P. 1 | | | | | | |
| Hori. | 2.4 | 2.9 | 1.7 | 1.8 | 3.4 | 5 |
| Vert. | 0.1 | 1 | 6.1 | 0.4 | 3.1 | 1.5 |
| S. P. 2 | | | | | | |
| Hori. | 0.5 | 0.3 | 3 | 0.4 | 1.9 | 2.9 |
| Vert. | 0.4 | 1.3 | 5.8 | 0.8 | 1.9 | 7.1 |
| S. P. 3 | | | | | | |
| Hori. | 1.4 | 1.2 | 2.8 | 1.6 | 3.2 | 2.6 |
| Vert. | 0.9 | 1.6 | 2.3 | 0.4 | 3.1 | 1.9 |
| S. P. 4 | | | | | | |
| Hori. | 1.6 | 0.9 | 0.6 | 1.7 | 3.2 | 1.1 |
| Vert. | 1.4 | 0.6 | 1.1 | 0.4 | 2.4 | 7.3 |
| S. P. 5 | | | | | | |
| Hori. | 1.6 | 1.7 | 0.6 | 0.3 | 1.3 | 4.7 |
| Vert. | 1.6 | 0.5 | 1.4 | 0.9 | 1.8 | 6.5 |
| S. P. 6 | | | | | | |
| Hori. | 2.0 | 1.4 | 1.1 | 1.1 | 2.7 | 2.6 |
| Vert. | 1.9 | 1 | 0.4 | 1.5 | 1.2 | 4.8 |
| Average | 1.3 | 1.1 | 2 | 1.2 | 2.3 | 3.9 |
| Hori. Ave. | 1.6 | 1.3 | 1.4 | 1.2 | 2.5 | 3.1 |
| Vert. Ave. | 1.0 | 0.9 | 2.6 | 1.2 | 2.1 | 4.7 |

( ) denotes the actual dimension error regarding the artificially introduced dimensional errors.
Table 2.7 Position estimation error of the six shear pockets for precast concrete panels I&II.

<table>
<thead>
<tr>
<th>Angular resolution (˚)</th>
<th>Precast Slab I</th>
<th>Precast Slab I</th>
<th>Precast Slab II</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.009</td>
<td>0.018</td>
<td>0.036</td>
</tr>
<tr>
<td>S. P. 1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hori.</td>
<td>2.3</td>
<td>2</td>
<td>2.4</td>
</tr>
<tr>
<td>Vert.</td>
<td>0.6</td>
<td>2.6</td>
<td>5.2</td>
</tr>
<tr>
<td>S. P. 2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hori.</td>
<td>0.1</td>
<td>0.3</td>
<td>0.6</td>
</tr>
<tr>
<td>Vert.</td>
<td>1.7</td>
<td>2.2</td>
<td>3.9</td>
</tr>
<tr>
<td>S. P. 3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hori.</td>
<td>1.4</td>
<td>1.4</td>
<td>2.4</td>
</tr>
<tr>
<td>Vert.</td>
<td>3.8</td>
<td>1.4</td>
<td>0.6</td>
</tr>
<tr>
<td>S. P. 4</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hori.</td>
<td>0.1</td>
<td>0.9</td>
<td>0.3</td>
</tr>
<tr>
<td>Vert.</td>
<td>2</td>
<td>1</td>
<td>3.6</td>
</tr>
<tr>
<td>S. P. 5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hori.</td>
<td>0.7</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>Vert.</td>
<td>0.3</td>
<td>0.4</td>
<td>2.1</td>
</tr>
<tr>
<td>S. P. 6</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hori.</td>
<td>1.9</td>
<td>1.9</td>
<td>0.3</td>
</tr>
<tr>
<td>Vert.</td>
<td>0.2</td>
<td>2.7</td>
<td>4.2</td>
</tr>
<tr>
<td>Average</td>
<td>1.3</td>
<td>1.4</td>
<td>2.2</td>
</tr>
<tr>
<td>Hori. Ave.</td>
<td>1.1</td>
<td>1.2</td>
<td>1.1</td>
</tr>
<tr>
<td>Vert. Ave.</td>
<td>1.4</td>
<td>1.7</td>
<td>3.3</td>
</tr>
</tbody>
</table>

( ) denotes the actual position error regarding the artificially introduced dimensional errors.

Table 2.8 Squareness estimation error of precast concrete panels I&II.

<table>
<thead>
<tr>
<th>Angular resolution (˚)</th>
<th>Squareness error (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.009</td>
</tr>
<tr>
<td>Precast Slab I</td>
<td></td>
</tr>
<tr>
<td>0.009</td>
<td>0.9</td>
</tr>
<tr>
<td>0.018</td>
<td></td>
</tr>
<tr>
<td>0.036</td>
<td></td>
</tr>
<tr>
<td>0.009</td>
<td></td>
</tr>
<tr>
<td>Precast Slab II</td>
<td></td>
</tr>
<tr>
<td>0.018</td>
<td>3.5</td>
</tr>
<tr>
<td>0.036</td>
<td></td>
</tr>
</tbody>
</table>

( ) denotes the actual squareness error regarding the artificially introduced dimensional errors.
Table 2.9 Manual inspection error of precast concrete panels I & II and their six shear pockets

<table>
<thead>
<tr>
<th>Precast Slab</th>
<th>Precast Slab I</th>
<th>Precast Slab II</th>
<th>Precast Slab I</th>
<th>Precast Slab II</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slab Hori.</td>
<td>1.5</td>
<td>0.0</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Slab Vert.</td>
<td>0.5</td>
<td>0.5</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>S. P. 1 Hori.</td>
<td>1.0</td>
<td>0.5</td>
<td>5.0</td>
<td>3.0</td>
</tr>
<tr>
<td>S. P. 1 Vert.</td>
<td>0.0</td>
<td>0.0</td>
<td>2.0</td>
<td>1.0</td>
</tr>
<tr>
<td>S. P. 2 Hori.</td>
<td>0.5</td>
<td>1.5</td>
<td>1.0</td>
<td>3.0</td>
</tr>
<tr>
<td>S. P. 2 Vert.</td>
<td>0.5</td>
<td>0.0</td>
<td>3.0</td>
<td>1.0</td>
</tr>
<tr>
<td>S. P. 3 Hori.</td>
<td>1.0</td>
<td>0.0</td>
<td>3.0</td>
<td>3.0</td>
</tr>
<tr>
<td>S. P. 3 Vert.</td>
<td>0.0</td>
<td>0.5</td>
<td>2.0</td>
<td>1.0</td>
</tr>
<tr>
<td>S. P. 4 Hori.</td>
<td>0.5</td>
<td>1.5</td>
<td>Position</td>
<td>Error (mm)</td>
</tr>
<tr>
<td>S. P. 4 Vert.</td>
<td>0.0</td>
<td>0.0</td>
<td>1.0</td>
<td>2.0</td>
</tr>
<tr>
<td>S. P. 5 Hori.</td>
<td>1.5</td>
<td>1.0</td>
<td>0.0</td>
<td>3.0</td>
</tr>
<tr>
<td>S. P. 5 Vert.</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>3.0</td>
</tr>
<tr>
<td>S. P. 6 Hori.</td>
<td>1.0</td>
<td>0.0</td>
<td>2.0</td>
<td>0.0</td>
</tr>
<tr>
<td>S. P. 6 Vert.</td>
<td>0.5</td>
<td>0.5</td>
<td>0.0</td>
<td>2.0</td>
</tr>
<tr>
<td>Average</td>
<td>0.6</td>
<td>0.4</td>
<td>1.6</td>
<td>2.2</td>
</tr>
<tr>
<td>Hori. Ave.</td>
<td>1.0</td>
<td>0.6</td>
<td>1.8</td>
<td>2.7</td>
</tr>
<tr>
<td>Vert. Ave.</td>
<td>0.2</td>
<td>0.2</td>
<td>1.3</td>
<td>1.7</td>
</tr>
</tbody>
</table>

2.6 Chapter Summary

This chapter describes an automated and non-contact technique that measures and assesses the dimensional qualities of precast concrete elements based on 3D laser scanning. A new edge and corner extraction technique was developed in this study, and successfully estimated the dimensional properties of the laboratory specimen and actual precast concrete elements. The experimental results demonstrate that the dimension, position and squareness estimation of the tested precast concrete elements are estimated within the 6 mm tolerance with a 95.2, 96.5 and 100 % success rate, respectively. In addition, the lessons learned from the results of the laboratory test are that: (1) scans under an incident angle of less than 45° is recommended for dimensional quality assessment of precast concrete panels; and (2) scans with a high scan density where the point-to-point distance of scan data is close to laser scanners’ measurement noise, should be avoided. Compared to other studies, this study has the following uniqueness: (1) the development and validation of an automated technique for dimensional QA of actual precast concrete elements; (2) the development of a fully-automated coordinate transformation edge extraction algorithms. However, the applicability of the proposed dimensional QA technique is limited to precast concrete elements with a rectangular-shape and uniform thickness in this study.
3 QUALITY ASSESSMENT TECHNIQUE II: SURFACE DEFECT ESTIMATION

3.1 Chapter Introduction

A surface quality assessment (QA) technique for precast concrete elements is presented in this chapter. Surface defects such as cracks, spallings and warping appear on the surface of a precast concrete element during the manufacturing or in-delivery stages due to inappropriate curing, sudden external loading or environmental changes (Portland Cement Association (PCA) 2001). These defects on a concrete surface may become severer as time passes and can reach the point the steel rebars inside the precast concrete become exposed and corrode, compromising the serviceability and safety of the structure. Furthermore, the consequence of poor surface QA of precast concrete elements can be expensive. It was reported that defects on concrete components during construction, such as cracks and local mass losses, could result in rework costs of up to 6-12% of the total construction costs (Josephson and Hammarlund 1999). Currently, the inspection of the surface defects of precast concrete elements is done manually by certified personnel similar to the dimensional assessment. Inspectors mostly use contact-type devices, such as a measuring tape or a profilometer, to identify the size and location of surface defects on the surface of a precast concrete element. A profilometer moves above the precast concrete surface in a predetermined pattern and measures the elevation of the surface, which is then compared to the as-designed elevations (Tang et al. 2011). However, the current surface QA methods are time-consuming and costly. To overcome these problems, this study develops...
a technique that can simultaneously localize and quantify spalling defects, which are a representative
defect on precast concrete surfaces with a 3D laser scanner. Defect sensitive features, which have
complementary properties to each other, are developed and combined for improved localization and
quantification of spalling defects. In order to verify the proposed surface QA technique, numerical
simulations and experiments are conducted. Furthermore, a parametric study with varying scan
parameters was performed for finding optimal detection conditions.

This chapter is organized as follows. First, the related literature is presented in Chapter 3.2,
followed by the development of the surface quality assessment technique in Chapter 3.3. Then, a
series of numerical simulation and laboratory tests are discussed in Chapters 3.4 and 3.5, respectively.
Actual experimental results implemented on real precast concrete slabs are presented in Chapter 3.6.
The discussing and chapter summary are then presented in Chapters 3.7 and 3.8.

3.2 Related Work

3.2.1 Vision camera-based surface quality inspection

The use of visual images is the most popular approach in detecting the exterior defects of a
structure because it is fast and inexpensive. For the detection of cracks, Hutchinson and Chen (2006)
proposed a probabilistic method based on Bayesian decision theory for automatic crack detection
from images. Barazzetti and Scaioni (2009) employed the RGB intensity to detect cracks, then
computed the crack width at a given cross-section. For the detection of air-pockets, Suwwanakarn et al. (2007) proposed the use of three circular filters to detect air pockets on the surfaces of concrete. For the detection of spallings, Koch and Brilakis (2011) proposed a technique using image segmentation and morphological thinning. While the image-based methods offer good accuracy, their
performance is heavily affected by lighting conditions. Furthermore, although identification of defect
sizes such as length, width, depth and volume is important for assessment of concrete structures, these
types of qualitative information cannot be retrieved using image-based methods without prior
knowledge such as the distance between a camera and a target structure or the size of a reference
target.
3.2.2 Laser scanning-based surface quality inspection

Using the point cloud data acquired from 3D laser scanner, researchers have proposed algorithms to detect and visualize defects on concrete surfaces. Teza et al. (2009) proposed a defect detection technique based on the computation of the mean and Gaussian curvatures of the surface. Tang et al. (2011) compared the detectability of surface flatness defects with different algorithms and scanners. Olsen et al. (2010; 2013) proposed a technique that analyzed the volumetric change of a reinforced concrete structure using I-Site Studio 3.0 software program and discussed the potential of integrating laser scan points with intensity images for recognizing complex defect patterns, respectively. Liu et al. (2011) proposed a distance and gradient based volume loss detection technique for an in-situ concrete bridge. Mizoguchi et al. (2013) estimated the depth of scaling defects based on a customized region growing approach. Despite the large volume of literature on laser scanning based defect detection of concrete surfaces, little attention has been paid to the simultaneous and quantitative estimation of surface defect location and volume loss. Moreover, there has been no logistic guidance for optimal scanning parameter selection, although it can be useful in practice. Thus, it is necessary to develop a technique that accurately localizes and quantifies surface defects, and identify an optimal scanning parameter for enhancing the detectability of precast concrete surface defects.

3.3 Surface Defect Quality Assessment Technique for Precast Concrete Elements

Fig. 3.2 (a) provides an overview of the proposed precast concrete spalling defect detection technique. Here, it is important to note that the term ‘spalling’ used in this study is defined as a deeper surface defect than scaling, often appearing as circular or oval depressions on surfaces (PCA 2001). The target object is assumed to be a rectangular precast concrete structure. The laser scanner is positioned at a certain distance from the target concrete structure and scans the concrete surface. First, a region of interest (ROI) is selected, and then the laser scanner captures the 3D coordinate information of the scanned points inside the ROI. Fig. 3.2 (b) shows the overall procedures for the proposed automated technique, which include coordinate transformation, defect localization and defect quantification. Note that the word ‘automated’, as used in this study implies that, once the raw scan data within a ROI becomes available, the proposed technique operates in a fully automated way for all data processing from coordinate transformation for defect quantification. Details for each step are described below.
Figure 3.2 Overview of the proposed precast concrete spalling defect detection technique: (a) Laser scanner configuration for precast concrete surface scanning; (b) Procedures for the proposed defect localization and quantification

3.3.1 Coordinate transformation

Once point cloud data is acquired from the laser scanner, their 3D coordinates with respect to the laser scanner are transformed to a new coordinate system with respect to the target object. The main purpose of this is to remove unwanted background scan points behind the target so that only scan points within the target surface are retained for data processing. The removal can be easily achieved after coordinate transformation by setting a proper region for the three axes of the new coordinate system.

Figure 3.3 Determination of three points of the target object from a range image for coordinate transformation: (a) The initial range image of a target specimen within a ROI; (b) Edge and corner detection using the canny edge detection and Hough transform in a binary image; (c) Determination of three points near the corners of the target object
Figure 3.4 Three point selection algorithm for automated coordinate transformation

For coordinate transformation, three pixel points near the corners of the target structure are automatically determined from the range image generated from the point cloud. Here, each pixel of the range image and each scan point are coupled so that each pixel of the range image holds the distance value from the laser scanner to the corresponding scan point. Also, at this stage, only pixel points ‘near’ the exact corners are identified and used for coordinate transformation because the range values of the exact corners have large measurement errors due to the mixed pixel problem (Hebert and Krotkov 1991). Fig. 3.3(a) shows the range image of the ROI of the target object. The target object closer to the laser scanner is shown in black while the background of the object is shown in white. In order to determine three pixel points near the corners of the target object, the exact corners of the target object are first extracted by intersecting the edge lines obtained from the Hough transform as shown in Fig. 3.3(b). Subsequently, the three pixel points used for coordinate transformation in Fig. 3.3(c) are determined using the proposed algorithm in Fig. 3.4. First, candidate pixel points surrounding each corner point (C1, C2, and C3) are limited to 1) the ones from each corner point within a certain margin bound (ε) and 2) ones with a range distance of less than the range threshold (γ). Note that ε and γ are selected to be 10 pixels and the mean range value of the range image such that only pixel points on the target object surface and 10 pixel distance from each corner point are selected as candidate pixel points. An iterative search for the best three pixel points is then performed based on the condition that the horizontal and vertical lines formed by the three scan points...
corresponding to the selected three pixel points are orthogonal in the 3D space. Note that the orthogonality condition between the two lines should be preserved to avoid the distortion of scan points after coordinate transformation. However, since a perfect right angle between the two lines might not be achievable due to the limited spatial resolution of the laser scanner, three pixel points forming the angle closest to a right angle are determined as shown in Fig. 3.3(c). Once the three scan points corresponding to the selected pixel points are extracted, the rotation and the translation matrices for coordinate transformation are determined, and the coordinates of all scan points are transformed with respect to the target object coordinate system. The unnecessary background scan points are then removed by setting a margin to each of the three axes of the new coordinate system such that only scan points on the target surface are retained for further data processing.

3.3.2 Defect-sensitive features

![Figure 3.5 Definitions of defect sensitive features: (a) Overview of scan points lying on a concrete surface (b) Definition of the angle deviation from the reference direction in the x-z plane view; (c) Definition of the distance deviation from the globally fitted plane in the x-z plane view](image)

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Once coordinate transformation and elimination of unwanted scan points are complete, defect localization and quantification processes ensue. In this study, two defect-sensitive features, i.e., angle deviation and distance deviation, are selected and combined to enhance the detectability on the entire region of spalling defects since each feature has unique yet complementary characteristics. Fig. 3.5 illustrates the definition of the two defect sensitive features. The angle deviation is defined as the angle difference between the normal vector of a locally fitted plane and the reference direction and the distance deviation stands for the distance difference between a scan point and the globally fitted plane. Fig. 3.5 (b) illustrates that the angle deviation from the reference direction increases as the scan point within the defect area moves closer to the defect edges. Therefore, the angle deviation is effective in identifying the defect boundaries. On the other hand, as shown in Fig. 3.5 (c), the distance deviation has a larger value near the center of the defect area rather than near the edges so that the distance deviation is effective in identifying the inside region of defects.

First, the angle deviation for each scan point is computed as follows:

1. The local plane of the $i$-th scan point $(p_i)$ is generated from its eight nearest neighboring points $(p_i^j, j = 1, ..., 8)$.

2. The covariance matrix $(C(p_i) \in \mathbb{R}^{3 \times 3})$ of the eight neighboring points is computed as:

   \[ C(p_i) = \frac{1}{8} \sum_{j=1}^{8} (p_i^j - \bar{p}_i) \cdot (p_i^j - \bar{p}_i)^T \]  

   (3.1)

   where $\bar{p}_i$ is the centroid of the eight neighboring points around $p_i$.

3. A principal component analysis (PCA) is performed on the covariance matrix to estimate a normal vector of the local plane (Shakarji 1998):

   \[ C(p_i) \cdot v_m(p_i) = \lambda_m(p_i) \cdot v_m(p_i), m \in \{1, 2, 3\} \]  

   (3.2)

   where $v_m$ and $\lambda_m$ stand for the $m$-th eigenvector and eigenvalue of the covariance matrix, respectively. Because the covariance matrix $(C)$ is symmetric and positive-definite, its eigenvalues are all real and non-negative. When the eigenvalues are arranged in ascending order ($0 \leq \lambda_1 \leq \lambda_2 \leq \lambda_3$), the first eigenvector $(v_1)$ corresponding to the smallest eigenvalue $(\lambda_1)$ approximates the normal vector $+n = \{n_x, n_y, n_z\}$ or its opposite $-n$. The ambiguity of the sign of the normal vector is
resolved by forcing the orientation of all normal vectors to an upward direction (+z axis).

(4) A defect index \( \text{DI}_1(p_i) \) for the first defect sensitive feature, i.e., the angle deviation from the reference direction, is defined as the average of the angle deviations of the eight neighbor points surrounding \( p_i \):

\[
\text{DI}_1(p_i) = \frac{1}{8} \sum_{j=1}^{8} \theta(p_{i,j})
\]  

(3.3)

where \( \theta(p_{i,j}) \) denotes the angle deviation of the \( j \)-th nearest point from the reference direction. Here, the reference direction is set to the +z direction perpendicular to the x-y plane. Note that \( \text{DI}_1 \) increases as the scan point within the defect area moves closer to the defect so that \( \text{DI}_1 \) is effective in identifying the defect boundaries.

As the second defect sensitive feature, the distance deviation of each scan point from a globally fitted plane is defined as illustrated in Fig. 3.4 (c). Here, the globally fitted plane is obtained by least-square fitting a 3D linear plane into all scan points within the target concrete surface. Then, the distance deviation of a scan point \( p_i \) from the global surface is computed as follows:

\[
\text{DI}_2(p_i) = \sqrt{\frac{a \cdot p_i(x) + b \cdot p_i(y) + c \cdot p_i(z) + d}{a^2 + b^2 + c^2}}
\]  

(3.4)

where \( a, b, c \) and \( d \) are the coefficients of the globally fitted plane \( (ax + by + cz + d=0) \). \( p_i(x) \), \( p_i(y) \) and \( p_i(z) \) are x, y and z coordinates of \( p_i \), respectively. Note that \( \text{DI}_2 \) typically has a larger value near the center of the defect area rather than near the edges as mentioned earlier. Therefore, \( \text{DI}_1 \) and \( \text{DI}_2 \) are complementary for defect localization.
3.3.3 Defect identification and quantification procedures

The defect identification and quantification procedures are described below and outlined in Fig. 3.6.

1) Subdivision of the target surface area: The entire surface area is virtually divided into a number of subdivisions. Since the spatial resolution of scan points within the target surface is not constant due to different scan parameters (scan distance and incident angle) for each scan point within the target surface, this subdivision process is necessary in localizing and quantifying spalling defects. Here, the size of each subdivision should be small enough to achieve high defect localization accuracy, but sufficiently larger than the spatial resolution of laser scanning. The effect of the subdivision size on the defect localization is investigated in the experimental test section.

2) Calculation of two defect indices for each scan point: Based on Eqs. (3.3) and (3.4), two defect indices, DI₁ and DI₂, are calculated for all scan points. Note that the global plane necessary for the calculation of DI₂ is obtained using all scan points over the entire target surface.

3) Calculation of two defect indices for each subdivision: Once two defect indices for all scan points are obtained, the defect indices for each subdivision are computed by averaging the defect index values of the scan points falling inside each subdivision. Hence, each subdivision holds two defect index values (DI₁(Sᵢ) and DI₂(Sᵢ)), where Sᵢ stands for the i-th subdivision.

4) Calculation of a unified defect index for each subdivision (DI(Sᵢ)): A unified defect index for each subdivision is defined as follows:

\[ DI(Sᵢ) = α \cdot DI₁(Sᵢ) + (1-α) \cdot DI₂(Sᵢ), \text{ } 0 < α < 1 \]  

(3.5)

where α and (1-α) are weighting factors for DI₁ and DI₂, respectively. In this study, an equal value of 0.5 is assigned to α and (1-α) such that same contribution to detection of a defect is given to DI₁ (the edge region) and DI₂ (the inner region). Note that DI₁ and DI₂ are combined here because they are complementary as discussed in the previous section. Therefore, the combined index preserves the individual advantages of the two indices. Here, it is important to note that each index is normalized by dividing its value with the maximum value among all subdivisions, so that each index ranges from 0 to 1.
5) **Calculation of a threshold** (TR): A threshold (TR) for defect diagnosis is computed from the intact subdivisions of the surface. There are two steps in determining a threshold value from the intact subdivisions. First, selection of candidate intact subdivisions is undertaken. Since the actual intact subdivisions are initially unknown, candidate intact subdivisions, with DI values lower than the threshold value associated with 95% confidence level from the Weibull distribution of all subdivision DI values, are determined. Note that the confidence level is selected based on two assumptions: 1) the surface area of intact subdivisions is much larger than that of defect subdivisions; and 2) the intact subdivisions have both low DI values. Once the candidate intact subdivisions are obtained, as the second step, each threshold (TR₁ and TR₂) for DI₁ and DI₂ is established with 99% confidence level from the Weibull distribution of DI₁ and DI₂ values obtained from the candidate intact subdivisions.
Finally, the unified threshold (TR) is obtained as follows:

\[
TR = \alpha \cdot TR_1 + (1-\alpha) \cdot TR_2
\]  

(3.6)

Note that the form (Eq. (3.6)) of calculating TR should be derived in the same from as that of Eq. (3.5) since the threshold is nothing but the defect index value corresponding to a certain statistical confidence interval. Also, it is important to note that the candidate intact subdivisions are iteratively updated through the recursive defect localization step (step 7)) and finally converged.

6) **Initial defect localization**: Once DI(S_i) and TR are computed, initial defect diagnosis is undertaken based on the following statement:

“If DI(S_i) exceeds TR, the corresponding subdivision (S_i) is diagnosed as damaged. Otherwise the subdivision is classified as healthy.”

7) **Recursive defect localization**: In this step, recursive defect localization is performed for improved defect localization. The initial defect localization result may not be accurate enough because the global plane necessary for the calculation of DI_2 may even include scan points from defect areas. To improve the defect localization accuracy, the global plane is re-fitted at this stage excluding the scan points within the defect areas identified in the previous step. Then, DI_2 is updated, and steps 3) to 6) are repeated until there is no difference between the previous and current defect localization results.

8) **Defect quantification**: Once all damaged subdivisions are identified, the total volume loss caused by defect is estimated by multiplying the size of each subdivision with the defect depth (the distance deviation of each subdivision from the global plane) and summing up this product over all damaged subdivisions.
3.4 Numerical Simulation

3.4.1 Numerical setup

The proposed concrete spalling defect localization and quantification technique was first validated through a numerical simulation. Fig. 3.7 shows the configuration of the numerical simulation model. In the simulation, it is assumed that the shape of laser beam is circular and the spatial resolution between two adjacent scan points is equal within the target surface. A 50 mm \( \times \) 50 mm virtual panel with a spatial resolution of 1 mm (total 2601 points) was generated to simulate a set of point cloud data lying on a concrete surface. Two different types of spalling defects, which are the most commons in practice, were considered: 1) concave-shape defect with dimensions of 10 mm \( \times \) 10 mm (defect I); 2) flat-top defect with dimensions of 10 mm \( \times \) 10 mm (defect II). A maximum thickness of 2 mm at the center of the defect and a uniform thickness of 2 mm were simulated for defects I and II, respectively. In order to examine the effect of the measurement noise of the laser scanner on defect localization and quantification results, Gaussian random noise with zero mean and five different levels of standard deviations (STD) (0.1, 0.2, 0.3, 0.4 and 0.5 mm) was added to all virtual scan points.

3.4.2 Simulation results

Fig. 3.8 shows the defect localization results from the numerical simulation. Note that the results are obtained with 0.3 mm standard deviation noise. Figs. 3.8 (a) and (b) show the effectiveness...
of DI\textsubscript{1} and DI\textsubscript{2} in detecting the edges and the inner regions of the defect areas, respectively. When the two defect sensitive features are combined, the overall detectability of the defects is enhanced as shown in Fig 3.8 (c). For the defect classification shown in Fig. 3.8 (d), a threshold value corresponding to a confidence interval of 99\% is used. Table 1 summarizes the results of defect localization and volume loss estimation with varying measurement noise levels. Note that all simulations are repeated 10 times, and the average results are reported.

To evaluate the defect localization performance of the proposed technique, recall and precision ratios are computed (Su 1999). Fig. 3.9 illustrates the definitions of these two ratios. The recall ratio represents the ratio of the correctly identified defect area (B) to the actual defect area (B+C), while the precision ratio denotes the ratio of the correctly identified defect area (B) to the detected defect area (A+B). For the evaluation of defect volume estimation performance, the volume estimation ratio is defined as the ratio of the estimated volume loss to the actual volume loss.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig3_8.png}
\caption{Defect localization results (numerical simulation): (a) Angle deviation from the reference direction (DI\textsubscript{1}); (b) Distance deviation from the globally fitted plane (DI\textsubscript{2}); (c) Combination of two defect indices (DI); (d) Defect classification (the red lines indicate the boundaries of the actual defect areas, and the regions with white color are the detected defect regions)}
\end{figure}
Figure 3.9 Definition of recall and precision ratios used for the evaluation of defect localization performance. Recall ratio represents the ratio of the correctly detected defect area (B) to the actual defect area (B+C), and the precision ratio denotes the rate of the correctly detected defect area (B) to the estimated defect area (A+B).

Table 3.1 Summary of defect localization and quantification results (simulation)

<table>
<thead>
<tr>
<th>Noise STD (mm)</th>
<th>Recall ratio (%)</th>
<th>Precision ratio (%)</th>
<th>Volume estimation ratio (%)</th>
<th>Recall ratio (%)</th>
<th>Precision ratio (%)</th>
<th>Volume estimation ratio (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>100.0</td>
<td>65.4</td>
<td>97.1</td>
<td>99.3</td>
<td>91.0</td>
<td>98.2</td>
</tr>
<tr>
<td>0.2</td>
<td>98.2</td>
<td>78.5</td>
<td>95.8</td>
<td>98.4</td>
<td>88.2</td>
<td>99.1</td>
</tr>
<tr>
<td>0.3</td>
<td>92.1</td>
<td>87.2</td>
<td>97.0</td>
<td>97.9</td>
<td>88.8</td>
<td>98.8</td>
</tr>
<tr>
<td>0.4</td>
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<td>95.3</td>
<td>95.8</td>
<td>92.8</td>
<td>96.2</td>
</tr>
<tr>
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<td>63.0</td>
<td>70.2</td>
<td>91.8</td>
<td>70.1</td>
</tr>
</tbody>
</table>

From Table 3.1, the following observations can be made: (1) As the noise level rises, the recall and volume estimation ratios decrease and the precision ratio increases. This trend is attributed to the fact that the threshold value is mainly affected by the noise level. With a lower noise level, the threshold value becomes lower and the defect size is overestimated. On the other hand, with a higher noise level, only severely damaged subdivisions inside a defect are detected, resulting in low recall and volume estimation ratios but a high precision ratio; (2) The overall best performance is obtained with a noise level of 0.3 mm; (3) The flat-top defect (defect II) is more easily detected than the concave-shape defect (defect I).
3.5 Laboratory Experiments

3.5.1 Laboratory specimen test configuration

![Image of laboratory test configuration and test specimen](image)

Figure 3.10 Laboratory test configuration and test specimen: (a) Test configuration; (b) Dimensions of the specimen and induced defects

Laboratory tests were conducted to further validate the proposed spalling defect localization and quantification technique. The overall test configuration and details of the test specimen are shown in Fig. 3.10. FARO Focus-3D was used for data acquisition (FARO 2014). The laser scanner was mounted on a tripod at a height of 1.5 m, which was the same height as the center of the test specimen as shown in Fig. 3.10 (a). A planar styroform with dimensions of 600 mm × 350 mm was used as the test specimen, and eight surface defects of varying sizes (10-100 mm) and depths (3-7 mm) were introduced at multiple locations on the specimen surface as shown in Fig. 3.10 (b). The eight defects were either flat-top (defects 1 to 4 in red color) or concave-shape (defects 5 to 8 in blue color). The subdivision size was selected to be 5 × 5 mm² for defect localization and quantification.

Table 3.2 presents the scan parameters used in laboratory testing. To examine the effect of scan parameters on the performance of the proposed technique, a total of 18 scans were conducted by varying the following scan parameters: 1) scan distance (4, 8, 12 m) between the laser scanner and the test specimen, 2) angular resolution (0.009, 0.018, 0.036°) of the laser scanner, and 3) incident angle (0, 15, 30°) between the laser scanner and the test specimen. The measurement noise of the laser scanner was 0.3 mm at 10 m based on the vendor specification. The total scanning time was around 72 minutes for 18 scans (average 4 minutes per scan). Note that the scanning time mainly depends on the selection of angular resolution, and scans with denser angular resolution (0.009°) required more time than scans with coarser angular resolution (0.018°).
### Table 3.2 Experiment scenario - laser scanning parameters

<table>
<thead>
<tr>
<th>Scan parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance</td>
<td>4m, 8m, 12m</td>
</tr>
<tr>
<td>Incident angle</td>
<td>0°, 15°, 30°</td>
</tr>
<tr>
<td>Angular resolution</td>
<td>0.009°, 0.018°</td>
</tr>
<tr>
<td>Measurement rate</td>
<td>976,000 points / second (0.009° angular resolution), 488,000 points / second (0.018° angular resolution)</td>
</tr>
<tr>
<td>Measurement noise (STD)</td>
<td>0.3mm @10m, 0.5mm @25m</td>
</tr>
<tr>
<td>Scanning time</td>
<td>Total 72 minutes for 18 scans</td>
</tr>
</tbody>
</table>

### 3.5.2 Laboratory Test Results

![Defect localization results](image)

**Figure 3.11** Defect localization results (laboratory test with 8 m scan distance, 0.009° angular resolution, and 0° incident angle): (a) Angle deviation from the reference direction (DL₁); (b) Distance deviation from the globally fitted plane (DL₂); (c) Combination of two damage features (DL); (d) Defect classification (the red lines indicate the boundaries of the actual defect area, and the regions with white color are the detected defect regions)
Fig. 3.11 shows the test results obtained with 8 m scan distance, 0.009° angular resolution, and 0° incident angle. Figs. 3.11 (a) and (b) show the different sensitivities of DI$_1$ and DI$_2$ to the boundaries and inner areas of the defects, respectively. Note that, to minimize the mixed pixel problem that occurred at the edges of the test specimen, both DI$_1$ and DI$_2$ at the specimen’s boundaries were set to zero. Like before, the localization performance was improved with the combination of the two defect indices (Fig. 3.11 (c)). Then, defect classification on each subdivision was undertaken (Fig. 3.11 (d)). Table 3.3 summarizes the defect localization and quantification with 18 sets of scan parameters. Note that each entry in Table 3.3 is the average value obtained for all eight defects. The following observations are drawn from Table 3.3: (1) The incident angle is the most critical parameter affecting the localization and volume estimation accuracy. In fact, the accuracy deteriorates as the incident angle increases from 0° to 30°; and (2) Increase of the angular resolution or the scan distance leads to a higher recall ratio and a lower precision ratio.

<table>
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<tr>
<th>Angular resolution (*)</th>
<th>Scanning distance (m)</th>
<th>Incident angle (*)</th>
<th>Recall ratio (%)</th>
<th>Precision ratio (%)</th>
<th>Volume estimation ratio (%)</th>
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<td>50.9</td>
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Chapter 3. Quality Assessment Technique II: Surface Defect Estimation

Figure 3.12 The effects of the scan parameters on defect localization: (a) Reference scan parameters (8 m distance, 0° incident angle, and 0.009° angular resolution); (b) 12 m distance; (c) 30° incident angle; (d) 0.018° angular resolution

Fig. 3.12 illustrates how the scan parameters affect the defect localization performance. The localization and quantification result for defect 5 is presented in Fig. 3.12 as a representative example. Comparison of Fig. 3.12 (a) with Fig. 3.12 (b) or (d) reveals that scan distance increase (12 m) or coarser angular resolution (0.018°) result in widening of the scan spacing and enhancement of the defect localization performance, particularly the recall ratio. This phenomenon can be explained as follows: As the scan spacing increases due to a longer scan distance or coarser angular resolution, the number of scan points lying inside each subdivision is reduced. Since the DI$_1$ of each scan point is determined by its eight neighboring points, the decreased scan points lying near edge subdivisions results in the increased sensitivity of DI$_1$ to the edge subdivisions of a defect. For instance, Fig. 3.13 (a) illustrates that the edge subdivision with a longer distance or coarser angular resolution has less scan points (2 intact and 2 defect points in this example) within the subdivision, and the corresponding DI$_1$ is more sensitive to edge defects because the DI$_1$ values of the points are affected by the defect points. On the other hand, the other edge subdivision with a short distance or denser angular resolution includes 9 scan points (6 intact and 3 defect points) within the subdivision, and results in a relatively lower DI$_1$ value since the left 3 intact scan points are not influenced by the defect points. As for the incident angle effect, Fig. 12 (c) shows that, as the incident angle increases
from 0° to 30°, the location of the estimated defect is shifted to the right of the actual defect. Fig. 3.13 (b) illustrates that, as the incident angle increase, the scan spacing becomes coarser and subdivisions at the edge region of the defect may not include any scan points. In addition, this phenomenon becomes more serious when the defect depth increases at the defect edges. Therefore, the scan spacing with respect to the subdivision size should be properly selected for optical defect localization and quantification performance.

**Figure 3.13** The effects of scan distance, angular resolution and incident angle on scan spacing: (a) The number of scan points within each subdivision decreases with a longer scan distance or coarser angular resolution; (b) With an increasing incident angle, subdivisions located at the defect edges may not have any scan points.
3.6 Actual Concrete Panel Test

![Figure 3.14 Test set-up and actual concrete panel: (a) Test configuration; (b) Dimensions of the specimen and induced defects](image)

To further examine the feasibility of the proposed localization and quantification technique for concrete spalling defects, an experiment was performed on an actual concrete panel with dimensions of 1200 mm × 900 mm × 150 mm. Fig. 3.14 shows the overall test configuration and the details of the concrete panel. The same laser scanner used for the laboratory specimen test was utilized and positioned at a fixed distance of 10 m from the concrete panel as shown in Fig. 3.14 (a). The concrete panel was fixed to a concrete wall, and the laser scanner scanned the panel at two different angular resolutions, 0.009° and 0.018°. Nine artificial spalling defects with different dimensions and depths were introduced on the concrete panel surface as shown in Fig. 3.14 (b). The defects were either flat-top (defects 1 to 5 in red color) or concave-shape (defects 6 to 9 in blue color). The size of each subdivision was chosen to be 5 × 5 mm² as before such that the whole surface area is divided into 43200 subdivisions.

Fig. 3.15 shows the defect localization results obtained with 0.009° angular resolution. As expected, Figs. 3.15 (a) and (b) show the effectiveness of each defect sensitive feature for detecting the edge and inner areas of the defects, respectively. Combining the two damage indices, enhanced defect localization results are obtained in Fig. 3.15 (c), followed by the defect classification (Fig. 3.15 (d)). The defect localization results show that all defects were successfully identified except defects 3 and 4, which has very small thickness deviations (3 and 2 mm). The manual inspection of the concrete panel revealed that the upper-left corner of the panel has a noticeable non-flat surface, and this non-
uniform surface condition attributed to difficulties in detecting shallow spalling defects (defects 3 and 4). Tables 4 and 5 show the defect localization and volume loss estimation results for the concrete panel, respectively. Note that each entry in Table 3.4 is the average value of the seven successfully localized defects. The recall and precision ratios are 91.9% and 88.9%, respectively. In Table 3.5, the average volume loss estimation ratio is 84.8% in the case of 0.009° angular resolution. The results demonstrate that the proposed technique is able to successfully locate and quantify all surface defects excepts defects 3 and 4.

![Figure 3.15](image-url) Defect localization results (concrete panel test): (a) Angle deviation from the reference direction (DI$_1$); (b) Distance deviation from the globally fitted plane (DI$_2$); (c) Combination of two defect indices (DI); (d) Defect classification (the red lines indicate the boundaries of the actual defect areas, and the regions with white color are the detected defect regions)

**Table 3.4** Defect localization results (concrete panel test)

<table>
<thead>
<tr>
<th>Scanning distance (m)</th>
<th>Incident angle (°)</th>
<th>Angular resolution (°)</th>
<th>Recall ratio (%)</th>
<th>Precision ratio (%)</th>
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<tr>
<td>10</td>
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<td>0.018</td>
<td>94.6</td>
<td>88.1</td>
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### Table 3.5 Defect volume loss estimation results (concrete panel test)

<table>
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<tr>
<th>Defect number</th>
<th>Aspects</th>
<th>Volume loss ($10^{-6}$ x m$^3$)</th>
<th>Estimation ratio (%)</th>
<th>Estimation average (%)</th>
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<td></td>
<td>Est.</td>
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<td>86.1</td>
<td>84.8</td>
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<td></td>
<td>Est.</td>
<td>304.4</td>
<td></td>
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<td>93.3</td>
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<td>8</td>
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<td>9</td>
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<td>68.3</td>
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<tr>
<td></td>
<td>Est.</td>
<td>1.3</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### 3.7 Discussion

All the simulation and test results presented in this study clearly indicate the importance of proper scan parameter selection. It is recommended that the scan distance, incident angle, and angular resolution be no more than 12 m, 15° and 0.018°, respectively, to achieve correct localization and volume loss estimation ratios of over 80% for spalling defects using the proposed technique. For example, if the laser scanner is 10 m away from a concrete structure, an allowed scan area corresponding to a maximum incident angle of 15° becomes 5.4 x 5.4 m$^2$.

Second, the relation between the subdivision size and scan spacing needs to be considered carefully. The size of the subdivision should be small enough to achieve precise defect localization, but sufficiently larger than the laser scan spacing. Theoretically, the subdivision size should be larger than the following scan spacing ($\Delta$):

$$\Delta = \frac{L \times \alpha_R}{\cos(\alpha_I)}$$  \hspace{1cm} (3.6)

where $L$ denotes the scan distance between the concrete surface and the laser scanner, and $\alpha_R$ and $\alpha_I$ denotes the angular resolution and the incident angle, respectively. For example, if the subdivision size is 5 x 5 mm$^2$, and $L$, $\alpha_I$ and $\alpha_R$ are set to 15 m, 30° and 0.018°, respectively, the scanning can be problematic because $\Delta$ (5.4 mm) is larger than the subdivision size. Based on the experiment results of
Chapter 3. Quality Assessment Technique II: Surface Defect Estimation

In this study, it is recommended that at least four scan points are included in each subdivision. Hence, the scan parameters should be carefully selected to ensure a good accuracy of spalling defect localization and quantification.

Third, scanning time needs to be also considered. The scanning time is mainly dependent on selection of angular resolution which dictates horizontal and vertical speeds of laser scanners. The size of a target structure also influences the scanning time. If scan parameters such as angular resolution and scan distance are assumed to be fixed, bigger size of target surface requires more scanning time than small size one. Hence, proper estimation of scanning time should be conducted prior to actual inspections for effective spalling defect detection.

3.8 Chapter Summary

This chapter presents a new surface QA technique that can simultaneously localize and quantify spalling defects on precast concrete surfaces using a laser scanner. Two defect sensitive features, which are complementary to each other, are proposed and combined for improved spalling localization and quantification performance. A defect classifier is also developed to automatically diagnose whether the investigated surface region is damaged, where the defect is located, and how large it is. Numerical simulations and experiments are conducted to demonstrate the effectiveness of the proposed defect detection technique. The results demonstrate that the proposed technique can accurately estimate the location and volume of concrete spalling defects. Furthermore, a parametric study with varying scan parameters of the laser scanner is performed for optimal scan parameter selection. The proposed technique can offer the following features: (1) Autonomous and simultaneous spalling defect localization and volume estimation on precast concrete surfaces, (2) Improved defect localization and quantification with combination of complementary defect sensitive features, and (3) Guidance for optimal scan parameter selection. In addition, based on the results obtained from actual precast concrete tests that the proposed surface QA technique can detect any spalling defect which is bigger than 3 mm in both length and depth. Currently the applicability of the proposed technique is, however, limited to flat concrete surfaces and two types of surface defects (concave and flat-top defects), and shallow spalling defects (less than 3 mm deep) can hardly be detected. Further investigation is needed in the following directions: (1) Extension of the applicability of the proposed technique to more complex structures and various types of defects, (2) Enhancement of the detectability on shallow defects, and (3) Integration of the laser scanner data with intensity images for more comprehensive analysis of spalling defects.
Chapter 3. Quality Assessment Technique II: Surface Defect Estimation
4 BIM-BASED QUALITY ASSESSMENT SYSTEM OF PRECAST CONCRETE ELEMENTS

4.1 Chapter Introduction

This study presents a systematic and practical system framework for dimensional and surface quality assessment (QA) of precast concrete elements using building information modeling (BIM) and 3D laser scanning technology. As precast concrete based rapid construction is becoming commonplace and standardized in the construction industry, checking the conformity of dimensional and surface qualities of precast concrete elements to the specified tolerances has become ever more important in order to prevent failure during construction. Moreover, as BIM gains popularity due to significant developments in information technology, an autonomous and intelligent quality assessment system that is interoperable with BIM is needed. The current methods for the dimensional and surface QA of precast concrete elements, however, rely largely on manual inspection and contact-type measurement devices, which are time-consuming and costly. In addition, systematic data storage and delivery systems for dimensional and surface QA are currently lacking. To overcome these limitations, this study aims to establish an end-to-end framework for dimensional and surface QA of precast concrete elements based on BIM and 3D laser scanning. The proposed framework is composed of four parts: (1) the inspection checklists; (2) the inspection procedure; (3) the selection of an optimal scanner and scan parameters; and (4) the inspection data storage and delivery method. In order to investigate the feasibility of the proposed framework, case studies assessing the dimensional and surface qualities of actual precast concretes are conducted.

This chapter is organized as follows. First, a review of the related literature is presented in Chapter 4.2, followed by a systematic framework development for the dimensional and surface QA of precast concrete elements in Chapter 4.3. Subsequently, case studies and their results for validating the feasibility of the proposed framework are presented in Chapter 4.4. Finally, this paper concludes with a summary and future work in Chapter 4.5.

4.2 Related Work

There are few studies on precast concrete BIM for efficient and effective data interoperability. One of them is work of the National Building Information Model Standard (NBIMS). NBIMS is a
joint project coordinated by the National Institute of Building Sciences (NIBS) and the buildingSMART Alliance. The goal of the project was to develop a national BIM standard for precast concrete design, engineering, fabrication and erection. The process of NBIMS consists of three major steps as shown in Fig. 4.1: (1) Define the user functional requirements needed for precast concrete design, fabrication and construction in a report, Information Delivery Manuals (IDM) that was prepared by a precast concrete BIM team and technical advisors led by Prof. Chuck Eastman at Georgia Institute of Technology; (2) Deliver and translate the IDM into an implementable specification for software vendors. In the project, the standard data model was selected as Industry Foundation Classes (IFC) schema; (3) Implement and test the exchange specifications. Here, the output of this step is a set of Model View Definitions (MVD) that define the exchange data needed to support the workflows defined in the IDM, covering the major digital exchanges dealing with precast concrete. However, these studies have focused only on the design and fabrication processes without QA of precast concrete element. Hence, this study proposes a framework for the dimensional and surface QA of precast concrete elements based on BIM and 3D laser scanning.
4.3 Development of a Framework for Dimensional and Surface QA of Precast Concrete Elements

![Diagram of 3D Laser Scanner and Precast Concrete](image)

**Figure 4.2** Overview of the proposed precast concrete quality assessment system combined with BIM and laser scanning: (a) Configuration for 3D laser scanning of a precast concrete element; (b) Two major modules within the proposed inspection system in relation to BIM

The objective of this study is to develop a holistic framework for laser scanning and BIM based automated inspection data storage and management of dimensional and surface qualities of precast concrete elements. Fig. 4.2 shows an overview of the proposed BIM and laser scanning based precast concrete QA system. In Fig. 4.2 (a), it is assumed that a precast concrete element is placed at a predetermined location and the laser scanner is positioned above the element and scans the whole surface of the panel in a single scan. Fig. 4.2 (b) shows two main modules of the proposed dimensional and surface QA system in relation to BIM, i.e., inspection and data management modules. For the inspection module, the following three issues should be clarified: (1) what the inspection checklists should be; (2) what the QA procedure should be employed; (3) which type of laser scanner is appropriate and which scan parameters are optimal for the intended QA checklists. For the data management module, one should determine how inspection information, including the inspection checklists, scan parameters and inspection results, is stored and delivered so that the system is interoperable with BIM. To answer the issues posed above, a systematic framework consisting of four parts is developed and described below.
4.3.1 Inspection checklists

Prior to performing precast concrete QA, it is essential to identify the inspection checklists - namely, what attributes of precast concrete elements need to be inspected with what degree of accuracy. In general, the construction specifications for a project play a major role in identifying the inspection checklists for precast concrete elements. These specifications detail the quality requirements for each precast component of the construction project, and these quality requirements can then be translated into inspection checklists. In this study, the inspection checklist is determined from the tolerance manual for precast and prestressed concrete as specified in the Precast Concrete Institute (PCI, 2000), and the guide for precast concrete wall panels from American Concrete Institute (ACI, 1998). Table 4.1 shows the determined inspection checklists, consisting of two categories - geometry and defects. For the geometry category, there are four dimensional features - dimension, position, straightness and squareness of precast concrete elements. Each dimensional feature has its own inspection checklists, called ‘attributes’. For example, length, width and thickness are the attributes for the feature ‘dimension’. The tolerance corresponding to each attribute varies with construction type, element type, length of the element and so on. In Table 4.1, tolerances for an exemplary precast slab of bridge deck are presented. Each dimensional attribute should be carefully inspected so that its value falls within the specified tolerance. Otherwise, the dimensional errors in each precast element can accumulate over the entire precast section. Within the defect category, there are four features - spalling, crack, warping and flatness. The ACI reports that these defects occur mainly due to improper concrete mixture proportions, careless curings as well as friction between the element and the mold form (ACI, 1998). The attributes for the defect features include the number, size, depth, length, width, area, location and volume of defects.

<table>
<thead>
<tr>
<th>Quality Category</th>
<th>Feature</th>
<th>Attribute (tolerance*)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Geometry</td>
<td>Dimension</td>
<td>Length (±6 mm); Width (±6 mm); Thickness (±6 mm)</td>
</tr>
<tr>
<td></td>
<td>Position</td>
<td>Length (horizontal (±6 mm), vertical (±6 mm))</td>
</tr>
<tr>
<td></td>
<td>Straightness</td>
<td>Size (±10 mm); Location</td>
</tr>
<tr>
<td></td>
<td>Squareness</td>
<td>Size (±3 mm); Location</td>
</tr>
<tr>
<td>Defect</td>
<td>Spalling</td>
<td>Number; Location; Area; Volume</td>
</tr>
<tr>
<td></td>
<td>Crack</td>
<td>Number; Depth; Length; Width (0.3 mm); Location</td>
</tr>
<tr>
<td></td>
<td>Warping</td>
<td>Number; Size (±6 mm); Location</td>
</tr>
<tr>
<td></td>
<td>Flatness</td>
<td>Number; Size (±6 mm); Location</td>
</tr>
</tbody>
</table>

* The tolerances are exemplary values for bridge deck precast concrete elements.
4.3.2 BIM and laser scanning based quality assessment procedure

Once the inspection checklists and desired tolerances are determined, an inspection procedure needs to be established. Fig. 4.3 describes the proposed dimensional and surface QA procedure for precast concrete elements using BIM and laser scanning. The QA procedure is composed of 4 phases:

(1) Supply: Suppliers manufacture the precast elements ordered for a given project and deliver the elements to an inspection site. It is important to note that the inspection site can be at a predetermined location in the manufacturing factory or at a certain location in the construction site. The suppliers also store the reference CAD model of each precast concrete element and their material and geometry properties, such as the concrete strength and dimensional tolerances of the precast elements in a BIM library.

(2) Preparation: Prior to the implementation of the QA, preliminary action on both the precast concrete element and the laser scanner is performed. This action includes the confirmation of the information of the precast element, inspection set-up, treatment for the precast elements and the...
selection of the optimal scan parameters of the laser scanner. Here, the confirmation of detail information of the precast concrete elements, which is stored in the BIM library, is ideally carried out through portable electronic devices such as smartphone or personal digital assistants (PDAs). Once the confirmation of the information of the precast element is completed, the precast element is sent to a designated location, and treatment processes such as the surface checking and cleansing of finished (hardened) precast concrete are undertaken before actual inspection. At the same time, the optimal scan parameters of the laser scanner are selected.

(3) Scan and inspection: Once the preparation for scanning is complete, data acquisition using the laser scanner is undertaken. In this step, the selection of the region of interest (ROI) is conducted with a coarse scan, followed by a dense scan for effective and accurate inspection. Once the raw scan data is acquired, data processing, which includes data cleansing and feature extraction, is conducted to automatically measure the intended inspection goals. Since the raw scan data has a high data capacity, data cleansing and feature extraction algorithms are needed for reducing data and computation cost. Subsequently, comparisons between the measured inspection results and the reference CAD model exported from the BIM library are conducted. At this stage, the inspection results are also delivered to and stored in the BIM library.

(4) Decision and delivery: At this stage, the decision of whether the discrepancies between the actual element and the reference model are within the tolerances in the inspection checklists is made. If any specific discrepancy exceeds the corresponding tolerance, disposal or rework of the precast element follows. Otherwise, the precast element is approved for use and delivered to a construction site for assembly. Here, the classification and detail information of the accepted and rejected elements are also accessible through the BIM library so that field engineers in the construction site can access and check the condition of the delivered precast concrete element via portable electric devices.

4.3.3 Selection of optimal scanner and scan location

The inspection quality depends largely on the specifications of a laser scanner such as laser source type, laser wavelength and operation principles. In addition, different inspection checklists may have different scanning requirements. For instance, checking the alignment of an anchor bolt attached to a precast concrete element may require a higher scanning resolution than simply identifying the existence of an anchor bolt. Therefore, the selection of the most appropriate laser scanner for a given project is critical for successful inspection. In this study, five criteria for the selection of a laser scanner are established as shown in Fig. 4.4:
Inspection tolerance: This refers to the limit of an acceptable discrepancy value (normally in mm) between the actual and the reference model for a specified inspection checklist. For example, the tolerance for length and width of a precast slab for bridge construction is ±6 mm according to the PCI (PCI 2000). Note that the tolerance which is project-dependent is the criterion first considered during the selection of an optimal laser scanner.

Accuracy: This refers to how close a measured value is to the actual (true) value. In laser scanning, this is often referred to as the ‘error’ in the range measurement. The accuracy of a laser scanner depends on its working principle. Typically, phase-shift laser scanners offer a relatively higher accuracy (up to 2 mm at 20 m) (FARO 2014) than time-of-flight (TOF) laser scanners (up to 4 mm at 100 m) (Olsen et al. 2010). Note that there is a condition for the optimal scanner selection that the accuracy of a laser scanner should be below the tolerance of inspection checklists.

Measurement range: This refers to an allowable scanning distance for the laser scanner. The measurement range is mainly affected by the working principle and laser source of the laser scanner. In general, TOF laser scanners have a longer measurement range (up to 6000 m) (RIEGL 2014) than phase-shift laser scanners (up to 120 m) (FARO 2014).

Price: In this study, it is assumed that the quality inspection of precast concrete elements is conducted using a commercially available laser scanner. The price of laser scanners ranges from $30,000 to $200,000 USD.

Scanning time: This refers to the time required to scan the desired inspection area. The scanning time depends mainly on the selection of a laser scanner’s angular resolution, which dictates horizontal and vertical scanning rate of the laser scanner. The scanning time is also influenced by the

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**Figure 4.4** Criteria for optimal selection of a laser scanner for precast concrete quality inspection
size of the target precast concrete element.

Depending on the goal of each checklist, different weighting on each aforementioned criterion can be assigned. For instance, for a dimensional QA, which requires a tolerance of ± 6 mm, accuracy, is the most important criterion for the laser scanner selection and thus a higher weighting can be given.

The scan parameters of a laser scanner should be optimized to obtain the best dimensional and surface quality inspection results. For the scanning of a precast concrete element, the scan distance and angular resolution are determined assuming that the laser scanner is positioned right above the center of the target precast concrete. These two parameters mainly govern the density of scan points. In general, the higher the density of the scan points is, the better the inspection results. However, a high density of scan points requires more scanning time and computing cost, which may not be allowed in real application. Hence, there is a trade-off between accuracy, cost and time when considering the inspection requirement of a project.

Since the dimensional quantities such as length, width and position of a target precast element may requires the extraction of features such as edges and corners from point cloud data, enough scan points should lie on both the edge and corner regions of the precast element. Furthermore,

![Figure 4.5 A mathematical model for the determination of the subdivision size, which is necessary for optimal detection of defects within a precast concrete element](image)

\[ L, S, W, \theta, \Delta \theta, H, d, s \]

*Figure 4.5* A mathematical model for the determination of the subdivision size, which is necessary for optimal detection of defects within a precast concrete element.
for the QA of defects such as spalling, warping and flatness, the scan region needs to be further divided into a number of subdivisions, and at least one scan point should fall inside each subdivision for localization and quantification of defects.

A mathematical model is developed to theoretically determine the minimum size of the subdivision considering the scanning distance and the angular resolution as shown in Fig. 4.5. For simplicity, the inspected precast concrete element is assumed to have a rectangular shape and a flat surface although the concept here can be generalized to more complex geometries. In the developed mathematical model, the maximum incident angle ($\theta$) and the maximum spatial resolution ($d$) of the laser scanner can be computed as:

$$\theta = \tan^{-1}\left(\frac{\sqrt{L^2 + W^2}}{2 \cdot H}\right) \quad (4.1)$$

$$d = \frac{\sqrt{L^2 + W^2}}{2} - H \cdot \tan(\theta - \Delta\theta) \quad (4.2)$$

where $H$, $L$ and $W$ are the laser scanner height (normal distance from the scanner to the target precast element), the length and the width of the precast element, respectively. Here, $L$ and $W$ are assumed known from the blueprint of the precast concrete element. $\Delta\theta$ denotes the angular resolution of the laser scanner. Note that a square shape is assumed for the subdivision, and the size is the length and/or width of the subdivision. As a result, the minimum size ($s$) of the subdivision covering the maximum spatial resolution ($d$) can be formulated as:

$$s = \frac{d \cdot L}{\sqrt{L^2 + W^2}} = \frac{L}{2} - \frac{L \cdot H}{\sqrt{L^2 + W^2}} \cdot \tan(\theta - \Delta\theta) \quad (4.3)$$

Note that Eq. (4.3) only specifies the minimum requirement, which may not be large enough for robust localization and quantification of defects. Therefore, a generous selection of scan parameters ($H$ and $\Delta\theta$) for determining the size of subdivision is recommended so that several scan points are included in each subdivision. Note that finding specific solutions for an optimal subdivision size and the number of scan points in a subdivision cannot be solved through only theoretical analysis and depend on many other factors such as surface roughness and reflectivity, is out of scope of this study.
In addition, the effects of the scanning parameters should be investigated for the selection of optimal scan parameters, as several studies show that a wrong selection of scanning parameters can have a negative impact on the results of quality inspections (Soudarissanane et al. 2011; Lichti 2007; Laefer et al. 2009). Among the scanning parameters, the incident angle, defined as the angle between the laser scanner and the scan point, is the key parameter affecting the measurement results. Laefer et al. (2009) recommended that scans with an incident angle of over 45° be avoided. Here, the scanning distance \( H \) is controlled so that the maximum incident angle \( \theta \) is less than 45°, i.e., \( H > \frac{\sqrt{L^2 + W^2}}{2} \).

### 4.3.4 Data storage and delivery method

To address data interoperability problems caused by differences in data format, IFC developed by BuildingSMART (2014) (formerly called the International Alliance for Interoperability (IAI)) is used as a delivery file format in this study. IFC was chosen here because (1) it is currently an open and neutral data format compatible with various BIM applications; (2) it is the only public

![Diagram](image.png)

**Figure 4.6** Schematic diagram of data storage and delivery for dimensional and surface quality assessment of precast concrete elements

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standard for building model data exchanges including object structure (topology), geometry and material and performance attributes; and (3) it has been found to be a promising candidate for effective exchange of geometry and other information of precast concrete (Jeong et al. 2009).

Fig. 4.6 illustrates the IFC based data storage and delivery scheme for dimensional and surface QA of precast concrete elements. All the data, from supply to delivery of the precast products, is created in the IFC format, then stored in and delivered to the BIM library through the cloud server. The cloud server serves bridges the participants of a project and allows them to reach the information whenever and wherever it is needed, and updating the information surely. Inspectors in charge of inspecting the quality of precast elements, for instance, can call up the material and geometry information stored in the BIM library via the cloud server. In addition, the inspectors can upload the scanning parameters they used and the inspection results in the format of IFC into the BIM library. Similarly, on-site engineers in the construction site can use tablets to access the inspection information for precise assembly of precast concrete elements.

Figure 4.7 IFC based entity relationship model for the precast concrete element quality inspection
Fig. 4.7 shows the IFC-based entity relationship model (ER model), which illustrates the association between different entities included in IfcPrecastElement, of a precast concrete element for quality inspection. The authors, based on the general scheme and properties of the latest IFC version (IFC 2×4), created the presented entities to overcome the absence of entities related to QA of precast concrete elements. The ER model consists of several entities and their attributes. The entity IfcQualityInspection, which is a sub-entity of IfcPrecastElement, consists of two sub-entities, IfcInspectionInfo and IfcInspectionResult. IfcInspectionInfo provides specific details regarding inspection preparation, such as laser scanning (IfcScanInfo), the design geometry of the inspected element (IfcDesignGeometry), and inspection checklist (IfcInspectionCriteria). The entity IfcScanInfo includes detailed information regarding scanning time (IfcScanTime), the laser scanner (IfcScanSensor) and the scanning parameters (IfcScanParameter). The other high-level entity in the quality inspection process is IfcInspectionResult, which contains the inspection results of the geometry (IfcInspectionDimensional) and defect (IfcInspectionDefect) quality for the precast element. The inspection result entities (IfcInspectionDimensional and IfcInspectionDefect) both provide quantitative values of the corresponding attributes defined in the inspection checklists of Table 1. For instance, the entity IfcInspectionSpalling has four quantitative attributes, which indicate how many (number) and how large (area and volume) the spalling defects are, as well as where (location) they are. Due to the limited space, not all attributes of the QA entity are included in Fig. 4.7.

4.4 Case Studies

To examine the applicability of the proposed framework to dimensional and surface QA of precast concrete elements, two case studies composed of dimension estimation and surface defect characterization were conducted on actual precast concrete elements.

4.4.1 Selection of inspection checklists and laser scanner

The inspection checklists were determined prior to the experiments. For dimensional estimation, three dimensional properties were estimated: (1) the dimensions (length and width) of the precast concrete element, (2) the dimension and positions of the shear pockets, which are rectangular holes within the precast concrete element, and (3) the squareness of the precast concrete element. The squareness error is defined as the difference in length between the longer sides of a precast component (PCI 2000). The surface defect characterization mainly targeted spalling defects, and four specific
checklists, the number, location, area and volume of defects, were established.

Once the inspection checklists were selected, an optimal laser scanner was then selected. Table 4.2 shows the specification of five commercially available laser scanners. As mentioned in Chapter 4.3.3, the primary criterion considered for laser scanner selection in this study was the accuracy of a laser scanner since the target tolerance for the dimensional QA was set to be 6 mm. The measurement rate (speed) and the price were also important considerations. In terms of the measurement range, all the candidate scanners satisfied the minimum requirement (20 m) of the measurement range. From these considerations, scanner no. 5, which offers the best accuracy, measurement rate and price was selected as the optimal laser scanner in this study.

**Table 4.2 Specifications of commercial 3D laser scanners**

<table>
<thead>
<tr>
<th>Scanner number</th>
<th>Maximum range (m)</th>
<th>Measurement rate (pts/sec)</th>
<th>Accuracy (mm)</th>
<th>Price (order)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>400 m</td>
<td>125,000 pts/sec</td>
<td>5 mm @ 100 m</td>
<td>1 (expensive)</td>
</tr>
<tr>
<td>2</td>
<td>350 m</td>
<td>5,000 pts/sec</td>
<td>7 mm @ 100 m</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>300 m</td>
<td>25,000 pts/sec</td>
<td>7 mm @ 100 m</td>
<td>4</td>
</tr>
<tr>
<td>4</td>
<td>300 m</td>
<td>50,000 pts/sec</td>
<td>4 mm @ 50 m</td>
<td>3</td>
</tr>
<tr>
<td>5</td>
<td>120 m</td>
<td>960,000 pts/sec</td>
<td>2 mm @ 20 m</td>
<td>5 (cheap)</td>
</tr>
</tbody>
</table>
4.4.2 Test specimens

![Precast Panel I](image1)

![Precast Panel II](image2)

**Figure 4.8** Test specimens for the dimensional estimation and surface defect characterization: (a) A photo and dimensions of the precast panel I used for dimensional estimation test; (b) A photo and defect dimensions of the precast panel II used for surface defect characterization test

Fig. 4.8 shows two test specimens used for the case study. Two precast panels (precast panels I and II) were designed and fabricated for dimensional estimation and surface defect characterization, respectively. The precast panels were fixed on a concrete wall and scanned by the laser scanner positioned at 10 m away from the panels, and scans with two different angular resolutions (0.009° and 0.018°) were conducted for both case studies. Here, the scanning distance and the angular resolutions, which dictates the density of scan points, were selected considering scanning time (around 3-5 minutes), point-to-point scan spacing (around 2-3 mm), the minimum size (s) of subdivision for precast panel II (1.26 mm for 0.009° angular resolution and 2.52 mm for 0.018° angular resolution) and maximum incident angle (5.71° for precast panel I and 3.43° for precast panel II). Precast panel I, used for dimensional estimation, has dimensions of 2000 mm (actually it has 1980 mm on one side) × 1000 mm × 150 mm and include six rectangular shear pockets as shown in Fig. 4.8 (a). Three dimensional errors were intentionally introduced to Panel I - a 20 mm loss of the upper horizontal dimension (1980 mm), a shift of No. 2 shear pocket right and downward by 25 mm and a shift of No.
6 shear pocket left and downward by 25 mm. Precast panel II, used for surface defect characterization, has dimensions of 1200 mm × 900 mm × 150 mm, and nine artificial spalling defects with different sizes and depths were induced on the surface of panel II as shown in Fig. 4.8 (b). The defects were either flat top (numbered from 1 to 5) or concave-shape (numbered from 6 to 9). Based the computed minimum size of subdivision from Eq. (4.3), the subdivision size of precast panel II for defect localization and quantification was selected as 5 mm for both 0.009° and 0.018° angular resolution cases.

4.4.3 Data analysis

The data-process procedures for dimensional QA were implemented after acquisition of a set of point cloud data from the selected laser scanner as followed.

**Step 1** – Coordinate transformation: The 3D coordinates of the scan data with respect to the laser scanner were transformed into a new coordinate system with respect to precast panel I. In this step, a 2D range image, where each pixel holds the distance value between the scan point and the laser scanner was generated from the scan data.

**Step 2** – Filtering: Unwanted background scan points positioned behind the precast panel surface were filtered out. Due to the coordinate transformation process, elimination of unwanted background scan points was implemented by setting a margin to each axis.

**Step 3** - Edge and corner extraction: An autonomous edge point extraction algorithm called ‘Vector-sum algorithm’ was implemented to extract only edge points along the horizontal and vertical edge lines of precast panel I. Once the edge points were extracted, the corners of the panel were identified by line fitting the edge points and finding the intersections between the fitted edge lines.

**Step 4** – Dimension estimation: The dimensions of precast panel I were initially estimated based on the extracted corner points. However, because of the mixed-pixel phenomenon of the laser scanner (Hebert *et al.* 1991), a phenomenon called edge loss occurs and the actual dimensions will always be underestimated. This underestimation caused by the edge loss was compensated based on an edge loss model (Tang *et al.* 2009). A more detailed explanation of the dimensional estimation steps is provided in Chapter 2.

As for the surface QA, The first two steps for surface defect characterization are identical to those of the dimensional QA. Defect identification, localization and quantification were then performed using two defect sensitive features: (1) angle deviation between the surface normal of a locally fitted plane and the reference direction, and (2) distance deviation between each scan point and
Chapter 4. BIM based Quality Assessment System of Precast Concrete Elements

a globally fitted plane. The data-process procedures were implemented after obtaining a set of point cloud data from the laser scanner as followed.

Step 3 - Subdivision of the target surface area: The entire surface area is virtually divided into a number of subdivisions. Here, the size of each subdivision should be small enough to achieve high defect localization accuracy, but sufficiently larger than the spatial resolution of laser scanning.

Step 4 – Calculation of two defect-sensitive features for each scan point: First, angle deviation is calculated. The eight nearest neighbors of a given scan point were identified based on the Euclidean distance, and the covariance matrix of the eight neighboring points was computed to estimate the normal vector of a local plane fitted by the eight neighboring points. Note that, the angle deviation index generally has a larger value near the edge of the defect area than the center region of the edges.

As the second defect sensitive feature, the distance deviation from a globally fitted plane was calculated. The globally fitted plane was obtained by least-square fitting a linear plane into all scan points within the surface of precast panel II. Here, the deviation index typically has a larger value near the center of the defect area than near the edges. Therefore, those two different indices are complementary each other for defect localization.

Step 5 – Unified defect index and threshold: Once the two defect indices for all the scan points were obtained, the defect indices (DI(S)) where S stands for the i-th subdivision, for each subdivision were computed by averaging the defect index values of the scan points falling inside each subdivision. In a similar manner, a threshold (TR) for defect diagnosis was computed from the intact subdivisions.

Step 6 – Initial defect diagnosis: An initial defect diagnosis was first undertaken based on the condition that if DI(S) exceeds TR, the subdivision (S_S) is diagnosed as defective otherwise the subdivision is classified as healthy.

Step 7 - Recursive defect localization: In this step, a recursive defect localization is performed for improved defect localization since the initial defect localization result may not be accurate enough because the global plane necessary for the calculation of distance deviation index may even include scan points from defect areas. To improve the defect localization accuracy, the global plane is re-fitted and the distance deviation index is updated until there is no difference between the previous and current defect localization results. Finally, once all damaged subdivisions are identified, the total volume loss caused by defect is estimated. A more detailed explanation on entire process of surface defect localization and quantification is provided in Chapter 3.
4.4.4 Test results and data storage and delivery

Figure 4.9 Results of edge and corner point extraction as part of dimensional estimation (obtained by scanning precast panel I with angular resolution of 0.009°)

Figure 4.10 Characterization results of surface defects on precast panel II (obtained with angular resolution of 0.009°): (a) Visualization of unified defect index (DI); (b) Defect classification result (the red lines indicate the boundaries of the actual defect areas, and the regions with white color are the detected defect regions)

Fig. 4.9 shows the edge and corner points obtained from scanning of precast panel I with angular resolution of 0.009°. The edge and corner points of the panel and six shear pockets were successfully identified. Table 3 summarizes the dimensional estimation results. Each entity in Table 4.3 is the estimated dimensional (dimension, position and squareness) value, and estimation error compared to the design value is presented in parenthesis next to each entity. The estimated upper lengths of the panel were 1978.9 mm and 1979.5 mm with the angular resolutions of 0.009° and 0.018°, respectively. These estimated upper lengths of the panel were 21.1 mm and 20.5 mm shorter than the design value (2000 mm), and agrees with the intended length loss (20 mm) with 1.1 mm and 0.5 mm error. The average dimension errors for all the entities with 0.009° and 0.018° angular
resolutions were 1.3 mm and 2.3 mm, respectively, and the average error values fall within the
tolerance (± 6 mm). With regard to the position estimation of the shear pockets, the intended shifting
of No. 2 and 6 shear pockets were well recognized and with the average estimation errors of 2.7 and
3.0 mm respectively. The average position errors of all the entities with 0.009° and 0.018° angular
resolutions were 2.1 mm and 2.4 mm, respectively. In terms of the squareness estimation, the
estimated errors were 23.5 mm and 23.5 mm with 0.009° and 0.018° angular resolutions, and close to
the exact squareness error value of 20 mm.

**Table 4.3** Dimensional estimation results from precast panel I

<table>
<thead>
<tr>
<th>Angular resolution (°)</th>
<th>0.009</th>
<th>0.018</th>
<th>0.009</th>
<th>0.018</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Upper Length</td>
<td>1978.9 (21.1)</td>
<td>1979.5 (20.5)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bottom Length</td>
<td>2002.4 (2.4)</td>
<td>2004   (4.0)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Width</td>
<td>995.9 (4.1)</td>
<td>998.6  (1.4)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>S. P. 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hori.</td>
<td>248.2 (1.8)</td>
<td>246.6  (3.4)</td>
<td>327.8 (2.8)</td>
<td>328.6 (3.6)</td>
</tr>
<tr>
<td>Vert.</td>
<td>149.6 (0.4)</td>
<td>153.1  (3.1)</td>
<td>277.6 (2.6)</td>
<td>278.9 (3.9)</td>
</tr>
<tr>
<td>S. P. 2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hori.</td>
<td>249.6 (0.4)</td>
<td>251.9  (1.9)</td>
<td>1026.1 (26.1)</td>
<td>1026.9 (26.9)</td>
</tr>
<tr>
<td>Vert.</td>
<td>150.8 (0.8)</td>
<td>151.9  (1.9)</td>
<td>299.2 (24.2)</td>
<td>300.5 (25.5)</td>
</tr>
<tr>
<td>S. P. 3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hori.</td>
<td>248.4 (1.6)</td>
<td>246.8  (3.2)</td>
<td>1675.1 (0.1)</td>
<td>1675.9 (0.9)</td>
</tr>
<tr>
<td>Vert.</td>
<td>149.6 (0.4)</td>
<td>153.1  (3.1)</td>
<td>274.5 (0.5)</td>
<td>274.2 (0.8)</td>
</tr>
<tr>
<td>S. P. 4</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hori.</td>
<td>248.3 (1.7)</td>
<td>246.8  (3.2)</td>
<td>326.9 (1.9)</td>
<td>327.6 (2.6)</td>
</tr>
<tr>
<td>Vert.</td>
<td>150.4 (0.4)</td>
<td>152.4  (2.4)</td>
<td>272.5 (2.5)</td>
<td>273.8 (1.2)</td>
</tr>
<tr>
<td>S. P. 5</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hori.</td>
<td>250.3 (0.3)</td>
<td>251.3  (1.3)</td>
<td>1002.1 (2.1)</td>
<td>1002.9 (2.9)</td>
</tr>
<tr>
<td>Vert.</td>
<td>150.9 (0.9)</td>
<td>151.8  (1.8)</td>
<td>273.9 (1.1)</td>
<td>274.7 (0.3)</td>
</tr>
<tr>
<td>S. P. 6</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hori.</td>
<td>248.9 (1.1)</td>
<td>252.7  (2.7)</td>
<td>1643.1 (31.9)</td>
<td>1643.9 (31.1)</td>
</tr>
<tr>
<td>Vert.</td>
<td>151.5 (1.5)</td>
<td>151.2  (1.2)</td>
<td>252.2 (22.8)</td>
<td>253.6 (21.4)</td>
</tr>
</tbody>
</table>

* S.P., Hori. and Vert. stand for ‘Shear Pocket’, ‘Horizontal’ and ‘Vertical’, respectively.
Table 4.4 Surface defect characterization results from precast panel II

<table>
<thead>
<tr>
<th>Angular resolution (°)</th>
<th>0.009</th>
<th>0.018</th>
<th>0.009</th>
<th>0.018</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Defect 1</td>
<td>Actual 324</td>
<td>346</td>
<td>349</td>
<td>486</td>
</tr>
<tr>
<td></td>
<td>Est. 144</td>
<td>164</td>
<td>168</td>
<td>72</td>
</tr>
<tr>
<td>Defect 2</td>
<td>Actual 254</td>
<td>281</td>
<td>287</td>
<td>254.5</td>
</tr>
<tr>
<td></td>
<td>Est. 164</td>
<td>168</td>
<td>276.4</td>
<td>288.8</td>
</tr>
<tr>
<td>Defect 5</td>
<td>Actual 281</td>
<td>287</td>
<td>276.4</td>
<td>288.8</td>
</tr>
<tr>
<td></td>
<td>Est. 164</td>
<td>168</td>
<td>254.5</td>
<td>288.8</td>
</tr>
<tr>
<td>Defect 6</td>
<td>Actual 178</td>
<td>181</td>
<td>150.8</td>
<td>167.8</td>
</tr>
<tr>
<td></td>
<td>Est. 177</td>
<td>181</td>
<td>150.8</td>
<td>167.8</td>
</tr>
<tr>
<td>Defect 7</td>
<td>Actual 133</td>
<td>136</td>
<td>160.7</td>
<td>154</td>
</tr>
<tr>
<td></td>
<td>Est. 133</td>
<td>136</td>
<td>160.7</td>
<td>154</td>
</tr>
<tr>
<td>Defect 8</td>
<td>Actual 28</td>
<td>29</td>
<td>18.9</td>
<td>1.9</td>
</tr>
<tr>
<td></td>
<td>Est. 27</td>
<td>29</td>
<td>18.9</td>
<td>1.9</td>
</tr>
<tr>
<td>Defect 9</td>
<td>Actual 3.8</td>
<td>6.5</td>
<td>1.3</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Est. 3.8</td>
<td>6.5</td>
<td>1.3</td>
<td>2</td>
</tr>
</tbody>
</table>

* Est. stands for ‘Estimated’.

Fig. 4.10 shows the localization results of spalling defects on precast panel II obtained with 0.009° angular resolution. The defect localization results show that all the defects were successfully identified except defects 3 and 4, which had small thickness deviations (3 and 2 mm). The manual inspection of the concrete panel revealed that the upper-left corner of the panel had a noticeable non-flat surface, and this non-uniform surface condition caused difficulties in detecting shallow spalling defects (defects 3 and 4). Table 4.4 summaries the defect estimation results for precast panel II. Note that Table 4.4 presents the detected area and volume loss values of the seven successfully localized defects. For defect area estimation, the average accuracies of 85.8 and 89.8 % for each angular resolution were obtained compared to the actual defect area. Here, the accuracy is defined as (actual area – estimated area) divided by actual area. As for the volume loss estimation of the detected defects, the average accuracies of 84.8 and 87.2 % for each angular resolution were obtained. The results demonstrate that the proposed laser scanning method can successfully locate and quantify surface defects except small defects where the thickness change is comparable to the measurement noise level of the laser scanner.
Figure 4.11 IFC representation of dimensional estimation results of precast panel I: (a) Hierarchical structure of IFC entities and attributes; (b) 3D BIM model of precast panel I with dimensional inspection results; (c) IFC data tree for the dimensional inspection results

Figs. 4.11 and 12 describe the IFC-based inspection data storage and delivery for dimensional estimation and surface defect characterization, respectively. The inspection results of Tables 4.3 and 4.4 were stored in the attributes of each IFC entity. For the dimensional estimation, all estimated dimensional values in Table 4.3 were stored in the corresponding attributes of the dimensional entities IfcDimension, IfcPosition and IfcSquareness as shown in Fig. 4.11 (c). For example, the estimated length and width of seven objects (panel I and six shear pockets) of precast panel I were stored in the attributes (length (#134) and width (#146)) of the IFC entity IfcDimension. Here, the ‘#’ refers to the line number of the IFC file. In addition, the dimensional abnormalities, which exceed the corresponding dimensional tolerances, were visualized with the error values as shown in Fig. 4.11 (b). Similarly, the detected spalling defect information of precast panel II were stored in the attributes (number, area, volume and location) of the IFC entity IfcSpalling as shown in Fig. 4.12 (c). For instance, the lines #276, #277, #10 and #6 in the IFC file of precast panel II indicate that seven spalling defects were detected and the corresponding defect area, volume loss and defect location were quantified.
Chapter 4. BIM based Quality Assessment System of Precast Concrete Elements

This chapter describes a holistic approach for dimensional and surface QA of precast concrete elements based on BIM and 3D laser scanning technology. To make the proposed approach practical and systematic, a detail framework consisting of four cores – (1) the inspection checklists, (2) the inspection procedure, (3) the selection of an optimal scanner and scan parameters, and (4) the inspection data storage and the delivery method was developed for QA of precast concrete elements. The applicability of the proposed framework with a 3D laser scanner was examined through assessing the dimensional and surface qualities of actual precast concrete elements. Furthermore, IFC-based inspection data storage and delivery method was validated using the estimated dimensional and surface quality assessment results. The experimental results show that the proposed BIM and laser scanning based quality assessment system has potential in autonomous and reliable QA of precast concrete elements. More specifically, the proposed method successfully estimated dimensions of a precast panel with average error of 2.5 mm and detected spalling defects on the surface of another panel with average localization and volume estimation accuracy of 86.9 % when the thickness change

Figure 4.12 IFC representation of surface defect characterization results of precast panel II: (a) Hierarchical structure of IFC entities and attributes; (b) 3D BIM model of precast panel II with defect characterization results; (c) IFC data tree for the defect characterization results

4.5 Chapter Summary

This chapter describes a holistic approach for dimensional and surface QA of precast concrete elements based on BIM and 3D laser scanning technology. To make the proposed approach practical and systematic, a detail framework consisting of four cores – (1) the inspection checklists, (2) the inspection procedure, (3) the selection of an optimal scanner and scan parameters, and (4) the inspection data storage and the delivery method was developed for QA of precast concrete elements. The applicability of the proposed framework with a 3D laser scanner was examined through assessing the dimensional and surface qualities of actual precast concrete elements. Furthermore, IFC-based inspection data storage and delivery method was validated using the estimated dimensional and surface quality assessment results. The experimental results show that the proposed BIM and laser scanning based quality assessment system has potential in autonomous and reliable QA of precast concrete elements. More specifically, the proposed method successfully estimated dimensions of a precast panel with average error of 2.5 mm and detected spalling defects on the surface of another panel with average localization and volume estimation accuracy of 86.9 % when the thickness change
of the spalling defect was over 3 mm. However, the proposed system has limitations, which are topics for future research. Firstly, the applicability of the proposed dimensional and surface quality assessment system is currently limited to precast concrete elements with a rectangular shape and a uniform thickness, and further investigation is needed to extend the applicability of the proposed system to other types of precast concrete elements that have more complex geometries. Second, quantitative analysis of selecting the optimal laser scanner and its scan parameters is out of the scope of this paper. Since data collection parameters and scanner selection may affect the data quality and accuracy of the dimensional and surface quality assessment for precast concrete elements (Tang and Alaswad 2012), quantitative analysis on the selection of optimal scanner and its parameters is needed. Third, the proposed dimensional and surface quality assessment technique is a sensor (i.e., laser scanner) and model dependent method, which is inevitably influenced by the measurement noise of the sensor and the uncertainty of the selected model. In future research, the accuracy of dimensional and surface QA can be improved through the development of optimized algorithms and analysis of the uncertainty of the model. Finally, the implementation of the inspection data storage and delivery of this study is limited to a single server scale, and the decision making process, which computes the discrepancy between the estimated dimensions and the corresponding design values, is not fully automated in this study. An efficient and effective data storage and delivery system based on cloud servers may become more attractive for future applications.
5 OPTIMAL SCAN PARAMETER SELECTION FOR ENHANCED QUALITY ASSESSMENT

5.1 Chapter Introduction

This chapter presents a method of selecting optimal scan parameters of a laser scanner for enhanced DQA technique of precast concrete elements. As described in Chapter 2, the performance of the DQA technique is largely influenced by scan parameters, and incident angle turned out to be the main factor among them. Hence, it is important to minimize the negative impact of incident angle on dimensional estimation accuracy. In order to meet this demand, this study aims to enhance the dimensional estimation accuracy of the DQA technique by optimizing the scan parameters of a laser scanner. To find an optimal scan parameter, a laser beam model, that simulates the position and the measurement noise of the laser beam of the laser scanner, is developed in this study. First, the mathematical equation of the laser beam position is derived based on the geometric relationship between the laser scanner and a target object. Then, estimation of the measurement noise of laser beam is conducted using an empirical approach since the theoretical measurement noise of a laser scanner is hard to be estimated due to different working principles and laser sources of laser scanners. Subsequently, validation of the proposed laser beam model is performed by comparing with experimental results. Then, parametric studies with different scanning geometry are followed using the developed model to find optimal scan parameters. It can be expected that the proposed DQA technique with accuracy enhancement via scan parameter optimization has a potential in achieving robust and accurate dimensional measurements of precast concrete elements.

This chapter is organized as follows. First, research background of laser beam including the measurement error source and the energy distribution of a laser beam is discussed in Chapter 5.2. The laser beam model developed for scan parameter optimization is then presented in Chapter 5.3. Validation of the proposed model and the scan parameter optimization result are discussed in Chapters 5.4 and 5.5, respectively. Finally, this chapter concludes with a summary and future work in Chapter 5.6.
Chapter 5. Optimal Scan Parameter Selection for Enhanced Quality Assessment

5.2 Research Background

5.2.1 Measurement error sources of laser scanners

High spatial resolution and fast capturing possibilities make 3D laser scanners popular in engineering settings. However, the quality of the individual points in the point cloud is not well investigated although it actually influences the quality of data processing outputs such as point cloud registration and segmentation. In fact, scans are subject to measurement noise despite the laser scanning data being highly accurate (in the range of 2-5 mm). Manufacturers often provide technical specifications of laser scanners, including its measurement accuracy, which is performed on reference surfaces under laboratory conditions. However, in practice, most target objects for laser scanning contain a variety of materials such as concrete, wood, and steel. In addition, different parts of the scenery are scanned with different scanning distances and incident angles, resulting in different levels of measurement errors. Also, environmental conditions including temperature, lighting conditions and humidity are often neglected, but may vary between scans during the survey.

Four main sources have been established as influencing the quality of individual scan points (Soudarissanane et al. 2010): (1) Scan mechanism; (2) Atmospheric conditions and environment; (3) Object properties and (4) Scanning geometry.

(1) Scanner mechanism – This includes internal (scan mirror alignment and laser beam divergence) and external (mounting) laser scanner settings. The misalignment of the laser mirror positioned inside the laser scanner can result in inaccurate range measurements. In previous studies, Zhuang and Roth (1995) investigated the scanner mechanism, focusing particularly on modeling the center offset of a laser mirror, and Lichti and Jantsho (2006) studied the influence of the beam divergence and angular resolution on the quality of scan points. Other studies investigated the mechanism of the detection process of the reflected signal (Adams and Probert, 1996; Pesci and Teza, 2008).

(2) Atmospheric conditions and environment – This includes the humidity, temperature, lighting conditions and pressure variations. These natural factors can affect the measurement error behavior of a laser scanner. In terms of the lighting conditions, Pfeifer et al. (2007) and Voisin et al. (2007) investigated the effect of darkness, artificial light and natural sunlight on measurement noise. The scanning environment, (e.g. indoors, outdoors), have been also studied by Borah and Voelz (2007).

(3) Object properties – This refers to the surface properties of the target object, concerning the anisotropy of the laser beam reflection that depends on the reflectivity and the roughness of the

(4) Scanning geometry – This refers to the placement of laser scanner relative to the location and orientation of the scanned surface, which determines the local incidence angle, local range and local point density of the laser points (Lindenbergh et al. 2005; Lichti 2007).

In this study, the first three factors were not considered for the following reasons. First, the measurement error caused by the scanning mechanism was neglected due to the assumption that the internal and external laser scanner settings were well configured. Second, according to a study that investigated the effect of atmospheric conditions and environment on measurement errors of laser scanners (Hejbudzka et al. 2010), the atmospheric conditions and environment were not considered in this study since the scans are carried out under scan distances of less than 20 m. Third, surface properties such as roughness and reflectivity can be negligible since target object is specified as only precast concrete elements and the surface can be assumed to have a high regularity. Therefore, scanning geometry containing the incident angle and scan distance was the main concern of this study for the estimation of the measurement errors of a laser scanner. The following section discusses the mathematical illustration of the signal deterioration with respect to the scanning geometry.

5.2.2 Signal deterioration with scanning geometry

![Signal deterioration with scanning geometry](image)

**Figure 5.1** Schematic illustration of different surface scattering models (Rees 2001)
Chapter 5. Optimal Scan Parameter Selection for Enhanced Quality Assessment

The intensity value of a received laser beam represents the amount of light reflected back to the scanner relative to amount of emitted light. The strength of the laser signal received by the scanner depends on the scattering behavior of the object surface. Six main types of reflectivity behaviors can be distinguished as illustrated in Fig. 5.1 (Rees 2001). Specular reflection occurs on a mirror-like smooth surface, and occurs when light from a single incoming direction is reflected into a single outgoing direction. In contrast to the specular reflection, Lambertian reflectance appears when the surface scatters the light in all directions. In practice, scattering behavior is often described by mixed models as the Minnaert model or the Henyey-Greenstein model that result from combining the Lambertian with the specular model. The geometric relationship between a laser scanner and an object surface determines the local scanning geometry. In this study, the ‘scanning geometry’ refers to the two components, i.e. incident angle ($\alpha$) and scan distance ($\rho$). If let the vector $P_i = [x_i, y_i, z_i]_{i=1...n}$ be the laser beam vector from the laser scanner to the object surface, the scan distance can be directly obtained as $\rho_i = \sqrt{x_i^2 + y_i^2 + z_i^2}$. The incident angle for $i$-th scan point, $\alpha_i$, which is defined as the angle between the laser beam vector $P_i$ and the normal vector $N$ of the surface can be formulated as:

$$\alpha_i = \cos^{-1}\left(\frac{P_i \cdot N}{|P_i| \cdot |N|}\right) \quad (5.1)$$

Note that the incident angle is always in the interval $[0 < \alpha_i < \frac{\pi}{2}]$.

**Figure 5.2** Schematic description of the energy distribution of a laser beam with different incident angle: (a) With a perpendicular laser beam ($\alpha = 0$); (b) With an incident angle $\alpha$ to the normal $N$ of a planar surface placed at a distance $d$. 
Fig. 5.2 shows the schematic illustration of the energy distribution of a laser beam with two different incident angles. A laser beam hitting a surface perpendicularly results in a circular footprint on the object’s surface. In this study, the laser beam is assumed to be a Gaussian beam (Alda, 2003), which means that the distribution of the energy in the footprint is normally distributed, as depicted on the left of Fig. 5.2. In the perpendicular case, the energy distribution is the same along all radial sections in the footprint, and a greater distance results in wider circular footprints and therefore weaker returned signals. On the other hand, if the laser beam is hitting the surface with a non-zero incident angle, the resulting footprint on the surface is elongated along a certain direction and therefore the energy distribution is also spread and forms an ellipse on the surface as shown in the right of Fig. 5.2. A lower intensity of received signal implies a deteriorating Signal to Noise Ratio (SNR). For longer distances or higher incident angles, the output signal is week and the detection of the signal becomes harder.

To quantify the amount of the received signal with respect to the emitted signal, the energy relationship between the laser light transmitter and the detection unit is described. According to the Bidirectional Reflectance Distribution Function (BRDF) (Jelalian 1992), the amount of received laser beam power with respect to emitted laser power can be formulated in free space path propagation as below:

\[ P_R(\rho) = P_T \cdot \frac{\cos \alpha \cdot \pi \cdot \gamma \cdot C_{sys} \cdot C_{atm}}{\rho^2} \]  

(5.2)

where \( P_R \) is the received power and \( P_T \) is the transmitted power. Note that Eq. (5.2) assumes that the surface hit by the laser pulse behaves in the form of a Lambertian scatter model, meaning the energy at the surface is scattered uniformly in all directions. \( \gamma \) denotes the surface reflectivity, and \( C_{sys} \) and \( C_{atm} \) refers to the constants of system and atmospheric losses, respectively. Since \( \gamma \), \( C_{sys} \) and \( C_{atm} \) can be assumed not to vary as mentioned earlier, only two variables (\( \rho \) and \( \alpha \)) are considered as the influence factors on the measurement errors of a laser beam. Hence, Eq. (5.2) shows that the SNR of a laser beam decreases with the increase in incident angles, and inversely proportional to the scan distance squared.
5.3 Laser Beam Simulation Model

5.3.1 Position modeling

As described in Chapter 2, the effect of the incident angle on the dimensional estimation results is closely related to the edge extraction performance of the DQA technique. In order to select an optimal scan parameter set for the enhanced dimensional estimation of the DQA technique, a simulation of the position of a scan point falling on the target object surface is necessary.

Modeling the position of laser beam was first conducted. Fig. 5.3 shows the geometric model for the y position of the laser beam on the target object surface. Note that the surface of the target object is assumed to be planar. With the line-of-sight characteristic of the laser scanner, the y position of the laser beam with horizontal angle of $H$ and vertical angle of $V$ on the object surface can be derived as:

$$y = d \cdot \frac{1}{\cos H} \cdot \tan V = d \cdot \frac{1}{\cos(\Delta H \cdot \theta)} \cdot \tan(\Delta V \cdot \phi)$$

where $d$ is the orthogonal scan distance between the laser scanner and the object. $\Delta H$ and $\Delta V$ denote the angular resolution in the horizontal and vertical directions, respectively. Similar to the $y$
position, the x position of the laser beam having the same horizontal and vertical angles (H and V) is calculated as:

\[
x = d \cdot \frac{1}{\cos V} \cdot \tan H = d \cdot \frac{1}{\cos(V \cdot f)} \cdot \tan(H \cdot i)
\]

(5.4)

### 5.3.2 Measurement noise modeling

Modeling of the measurement noise for each scan point was then performed to reflect the actual position of each scan point with measurement noise. Here, the measurement noise is defined as the standard deviation of the distance values of scan points from the best-fit plane generated about the scan points. A few previous studies (Lichti 2007; Soudarissanane et al. 2011) have investigated the measurement noise of laser scanners and attempted to make a model for the measurement noise,

![Figure 5.4 Procedures for the proposed measurement noise modeling](image)
estimating the actual measurement noise for a scan point is still inaccurate and the models are limited to laser scanners used in those studies. To tackle these limitations, this study proposed an empirical method of modeling the measurement noise of a laser scanner, which can be adapted to other types of laser scanners. Fig. 5.4 describes the process of the proposed measurement noise modeling. It is important to note that the proposed empirical modeling method is based on the actual measurement noise values obtained from multiple scan sets. There are four steps for the measurement noise modeling as follows:

(1) Collection of “multiple” base scan data sets with different scanning geometry and calculation of its measurement noises for each set – In this step, acceptable scan distances and incident angles are selected according to the size of precast concrete elements being scanned, and multiple base scan sets are obtained within the selected ranges of the scan distance and incident angle. For example, if the length of a precast concrete element is 10 m, the acceptable ranges of scan distance and incident angle for the base scan sets would be 5-15 m and 0-50°, respectively. Note that this selection is based on the assumption that the maximum incident angle between the laser scanner and the precast concrete element is below 45°. The measurement noise for each base scan is then computed using a planar fitting algorithm, i.e. total least squares. Here, the measurement noise (E) is defined as the standard deviation of the distance values of scan points from the best-fit plane generated about the scan points. The linear regression determined by the total least squares method minimizes the orthogonal distances from the point cloud of a scan to the fitted model (Hartley and Zisserman 2003). Using matrix notation, the equation of a plane is expressed as:

\[ \mathbf{Ax} = \mathbf{0}_{n \times 1} \]  

(5.5)

where the matrix of known observables is defined as \( \mathbf{A} = [\mathbf{P}, \mathbf{1}_{n \times 1}] \). Here, \( \mathbf{P} \) is the matrix of the set of test scan points, \( \mathbf{P}_i = [x_i, y_i, z_i]^T \) \( i=1...n \). The unknown parameters are denoted as \( \mathbf{x} \) which consists of four coefficients of the fitted plane. Here \( \mathbf{0}_{n \times 1} \) denotes the zero matrix. The solution \( \hat{\mathbf{x}} = [a, b, c, d] \) of the total least squares estimation of the planer parameters minimizes the sum of the squared orthogonal distances to the fitted plane. The residuals \( \hat{\mathbf{e}}_d \) of the fitted plane and the measurement noise (E) for each scan can be computed as:

\[ \hat{\mathbf{e}}_d = \mathbf{A}\hat{\mathbf{x}} \]  

(5.6)
\[ E_i = \sigma_{\hat{d}} \text{ where } i = 1, \ldots, n \] (5.7)

Hence, the implementation of Step (1) results in three nominal values for each base scan set, i.e. scan distance (\( \rho \)), incident angle (\( \alpha \)) and measurement noise (\( E \)).

(2) Collection of a ‘single’ set of test scan points – In this step, the entire surface of a target precast concrete element is scanned and a set of point cloud data is acquired. In the point cloud, all scan points have different scan distances and incident angles so the measurement noise for each scan point needs to be estimated based on the base scan data sets collected in Step 1.

(3) Selection of two closest base scan data sets to each scan points of test scan set – In this step, the two closest base scan data sets to each scan point of the test scan set are determined for measurement noise estimation.

(4) Estimation of the measurement noise for each scan point based on linear interpolation – The last step for the measurement noise modeling, the construction of a measurement noise value for each scan point is performed by interpolating the measurement noises of the selected two base scan data sets. Once the interpolation process is completed, all scan points within the precast concrete element have its own measurement noise value so that actual position estimation of laser beams considering the measurement error is realized.

Figure 5.5 Test set-up for collection of base scan sets for measurement noise modeling
For the measurement noise modeling, a series of scans with different scan distance and incidence angle were conducted, which corresponds to Step 1 of Fig. 5.4. Fig. 5.5 shows the experimental set-up for the collection of the base scan data sets. A laser scanner, Focus-3D (FARO Inc. 2014), and a lab-scale precast concrete panel with dimensions of 600 mm x 450 mm were used for the data acquisition. The test specimen was mounted on a table via a screw clamp mechanism with a goniometer enabling the mechanism to rotate horizontally with a precision of 2°, as depicted in Fig. 5.5. The specimen was placed at distances ranging from 1 to 16 m with an increment of 1 m and rotated from 0° to 70° in 10° increments. The surface of the precast concrete specimen was scanned at each scan set such that a total of 128 scans were done for the collection of base scan data. For each scan, measurement noise was estimated by using the obtained scan points and interpolation method. For each scan, at least 5000 scan points are used for the plane fitting in this study.

Fig. 5.6 shows the measurement noise results with increasing scan distances and incidence angles, which were computed based on the collected base scan data sets. It can be seen that there are two main trends. First, the level of the measurement noise over a scan distance of 8 m increases as the scan distance increases. Second, larger incidence angles cause larger measurement noise on the laser scan points. These observations are in accordance with Eq. (5.2).

Based on the calculated measurement noise values for the base scan data sets, the estimation of measurement noise for each scan point of test scan data was carried out by 1) selecting two closest base scan data sets to the scan point and 2) constructing the interpolated measurement noise using the selected two ranges. Once the measurement noise is estimated, the process of decomposing the measurement noise into those of three axes (x, y and z) is performed so the position model considers the measurement noise of scan points for all axes. The decomposed measurement noise for each axis

![Figure 5.6 Measurement noises with increasing scan distance and incident angles](image)
can be presented as:

\[ E_{x,i} = \frac{x_i}{S_i} \cdot E_i, \quad E_{y,i} = \frac{y_i}{S_i} \cdot E_i, \quad E_{z,i} = \frac{z_i}{S_i} \cdot E_i \] (5.8)

Finally, modeling for the laser beam position is completed with combination of the geometric model of laser beam (Chapter 5.3.1) and it’s measurement noise. In the following sections, the proposed laser beam model is validated by comparison with the experimental data, and selection of optimal scan parameters of the laser scanner is discussed.

5.4 Validation of the Laser Beam Model

In this section, the validation of the proposed laser beam model was performed by comparing the edge extraction results of the simulated scan points with experimental data. Fig. 5.7 shows the edge extraction performance in both the simulation model and the experimental test. Note that both results are the outcome of the ‘vector-sum’ algorithm implementation of the DQA technique. In the case of 0° incident angle, clear edge extraction results are obtained in both the simulation and experimental tests. On the other hand, in the case of 30° incident angle, the edge extraction results are relatively poor compared to the 0° incident angle due to the position irregularity of the scan points. Table 5.1 summarizes the quantitative results of the edge extraction performance comparison between the developed laser beam model and the experiment. In the table, the accuracy of edge extraction is defined as the vector-sum algorithm performance, which was calculated as (detected edge points + detected non-edge points) / total scan points. An average difference of 2.5 % between the developed model and the experiment was obtained, indicating that the developed laser beam model can accurately simulate the actual position of laser beam.

![Figure 5.7](image)

**Figure 5.7** Comparison of edge extraction performance between the proposed laser beam model and the experiment results in cases of incidence angle 0° and 30°: (a) Simulation and (b) Experiment
Table 5.1 Validation of the proposed laser beam model with varying scan parameters

<table>
<thead>
<tr>
<th>Angular resolution (°)</th>
<th>Distance (m)</th>
<th>Incident angle (°)</th>
<th>Simulation accuracy (%)</th>
<th>Experiment accuracy (%)</th>
<th>Difference (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>8</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
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<td>0</td>
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<tr>
<td></td>
<td></td>
<td>15</td>
<td>99.67</td>
<td>99.89</td>
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</tr>
<tr>
<td></td>
<td></td>
<td>30</td>
<td>87.14</td>
<td>93.87</td>
<td>6.73</td>
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<td>66.48</td>
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<td>99.97</td>
<td>99.99</td>
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<td></td>
<td>45</td>
<td>79.25</td>
<td>67.12</td>
<td>8.13</td>
</tr>
</tbody>
</table>

5.5 Selection of Optimal Scan Parameter

Fig. 5.8 describes the tested virtual precast concrete specimen used for the scan parameter optimization. The specimen with dimensions of 4800 mm × 1000 mm × 150 mm has eight shear pockets on the surface, and each identical shear pocket has 300 mm × 200 mm sizes. The objective of this simulation test was to find the optimal scan parameters to give the best dimensional estimation result for the dimension and the position of the tested specimen and the eight shear pockets is obtained. In this simulation, scan distances ranging from 4 m to 12 m with 0.25 m increments and angular resolutions ranging from 0.015° to 0.036° with and increment of 0.003° were investigated. The range was selected based on the assumption that the maximum incident angle of laser beam is below 30°.

Figure 5.8 Tested virtual precast slab specimen for selection of optimal scan parameters
Figure 5.9 Visualization of the dimension estimation result of the simulation test: (a) Dimension error plot in 3D; (b) Dimension error plot in 2D; and (c) Classification result of optimal scan parameter

Table 5.2 Dimensional estimation results with varying scan parameters for the simulation

<table>
<thead>
<tr>
<th>Angular resolution (°)</th>
<th>Distance (m)</th>
<th>Dimensional error (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Dimension</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>6.2</td>
</tr>
<tr>
<td></td>
<td>5</td>
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<tr>
<td></td>
<td>8</td>
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<tr>
<td></td>
<td>9</td>
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<td></td>
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<td>3.1</td>
</tr>
<tr>
<td>0.036</td>
<td></td>
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</table>
Fig. 5.9 shows the visualization of the dimensional estimation of the simulation test. The red pixels in Fig. 5.9 (b) indicate scan cases over the dimension error of 1.5 mm, while the blue pixels indicate the scan cases less than the dimension error of 1.5 mm. It can be summarized from the result as follows: (1) In cases of high point density (combination of low scan distance and angular resolution) such as the case of scan distance of 4 m and angular resolution of 0.015°, the dimensional errors are relatively large compared to cases of mid-level point density. Here, point density can be defined as ratio of the number of scan points to a unit region; (2) In the cases of low point density such as the condition of scan distance of 12 m and angular resolution of 0.036°, the dimension errors are also larger than mid-point density. Table 5.2 summaries the dimensional estimation results of the tested specimen with varying scan parameters. It is noted that due to the space limitation, only results for two angular resolutions of 0.015° and 0.036° are shown in Table 5.2. It can be seen that there are different trends between two different point density cases. The reason behind these phenomena is illustrated in details in Chapter 2.4.2.

The scan parameter selection, however, only provides safe scanning regions for the size of the tested specimen, which means that the safe scanning regions may change depending on the size of precast concrete elements being investigated. Thus, a method that can provide a general solution of selecting optimal scan parameters is needed. To this end, in this study two features, which are sensitive to the dimensional estimation error, are used to determine the optimal scan parameters in a general way regardless of the size of precast concrete elements. The features are (1) the average spatial resolution of the scan points and (2) the maximum incident angle between the laser scanner and the precast concrete element. These two features are selected based on the observation that the dimensional estimation errors are largely dependent on the point density of scan points as discussed in the previous paragraph and the measurement noise is largely influenced by the incident angle. The two features can be computed as:

\[
\text{Feature I} - \Delta = \frac{D \times \alpha_R}{\cos(\alpha_I)} \quad (5.9)
\]

\[
\text{Feature II} - \alpha_{I,max} = \tan^{-1}\left(\frac{\sqrt{L^2+W^2}}{2 \cdot D}\right) \quad (5.10)
\]

where \(D\) is the orthogonal scan distance between the laser scanner and a precast concrete element. \(L\) and \(W\) denote the length and the width of the precast concrete element, respectively, and are assumed known from the blueprint of the precast concrete element.
Fig. 5.10 shows the classification results of optimal scan parameter selection in the domain of two features. It is observed that the combined conditions of a high maximum incident angle and a low spatial resolution had large dimensional errors. For example, in the combined cases of over maximum incident angle of 20° and below spatial resolution of 2.5 mm, the classification indicates unsafe scan parameters for the DQA technique. In addition, the cases of a relatively large spatial resolution scan of over 4 mm, even in small maximum incident angles, were classified as improper scan parameters. In summary, the following recommendation can be derived from the simulation test when selecting scan parameters for DQA technique.

\[ 2.5 < \Delta < 4 \text{ mm and } \alpha_{\text{max}} < 25° \]  

Even though the proposed simulation model was developed based on a certain type of laser scanner, this approach can be adopted to other laser scanners for DQA of precast concrete elements. However, in this study, scanning time was not considered for the optimal scan parameter selection. To find the best scan parameter set for the DQA technique, further study considering scanning time will be investigated.
5.6 Chapter Summary

This chapter presents a method of selecting optimal scan parameters of a laser scanner for enhanced DQA technique of precast concrete elements. As described in Chapter 2, the performance of the DQA technique is largely influenced by scan parameters, and incident angle turned out to be the main factor. Hence, it is important to minimize the negative impact of incident angle on dimensional estimation accuracy. In order to meet this demand, this study aims to enhance the dimensional estimation accuracy of the DQA technique by selecting optimal scan parameters of a laser scanner. To achieve this goal, a laser beam model, that can simulate the position and the measurement noise of the laser beams of the laser scanner, is developed. First, the mathematical equation for the laser beam position is derived based on the geometric relationship between the laser scanner and a target object. Then, estimation of the measurement noise of laser beam is conducted using an empirical approach. Subsequently, validation of the proposed laser beam model was performed through comparison with experimental results. The validation result demonstrates that the proposed model can estimate accurately the position and the measurement noise of laser beams. Parametric studies with different scanning geometry are followed based on the developed model to find optimal scan parameters. Recommendations are derived from the simulation test, but further studies considering scanning time optimizing scan parameters need to be complete.
6 APPLICATION TO FULL-SCALE PRECAST CONCRETE ELEMENTS

6.1 Chapter Introduction

Until now, the validation results of the proposed DQA technique on only lab-scale specimens were presented. However, these validation results are not enough to prove the effectiveness of the proposed DQA technique. In addition, in the previous chapters, there was no validation test on how the obtained QA data was actually stored and managed in BIM. Thus, this chapter investigates the feasibility of the proposed methods for QA of precast concrete elements. The main objectives of this study are (1) full automation and additional of the DQA technique for real and complex field applications and (2) development of a cloud-BIM system for effective data storage and management of the estimated dimensional quality information. Different types of two full-scale precast slabs were used in this study and associated implementation issues are discussed. First, a new coordinate transformation algorithm is developed to make the DQA technique fully automated so that large-scale application can be successfully accomplished. Second, a new geometry matching technique that ties the precast slab models constructed from the scanner data with the built-in BIM model is developed for precise estimation of errors between the BIM model and the actual precast slabs. Third, the performance of the proposed DQA technique is compared with a conventional deviation analysis technique. From the comparison results, the average dimensional error for the proposed technique is 3.2 mm, while that of the conventional deviation analysis is 9.4 mm, demonstrating that the proposed technique can have high potentials in estimating and assessing the dimensional properties of the precast concrete element. This chapter is organized as follows. First, the configuration and test results of the field test are described in Chapter 6.2. The proposed cloud-BIM platform and validation results for effective data storage and management are presented in Chapter 6.3. Finally, this paper concludes with a brief summary and future work.
6.2 Full-scale Application of Dimensional Quality Assessment Technique

6.2.1 Test configuration

Figure 6.1 Test configuration of the full-scale dimensional QA: (a) Test set-up; (b) Top view of the inspected precast slabs

Figure 6.2 Blueprint (top view) of the precast slab type I and II
The experimental configuration of the field test is shown in Fig. 6.1. The field test was conducted in a precast manufacturing company located in Gim-Je in Republic of Korea. In the field test, a set of point cloud data was acquired from the test specimens using a phase-shift laser scanner, FARO Focus-3D (FARO 2014) shown in Fig. 6.1 (a). The laser scanner was positioned 9 m from the center of the target precast slab, and was fixed on the top of a crane. Table 6.1 shows the details of the scan parameters investigated and the tested two precast slabs. For data acquisition, three different angular resolutions (0.018, 0.036 and 0.072°) were investigated and the scanning times for each angular resolution case were measured at around 25, 8 and 4 minutes, respectively. In the field test, two types of precast slab were scanned as shown in Fig. 6.2. For the precast slab type I, the dimensions are 10,610 mm × 1,980 (1956) mm × 240 mm and it has 16 shear pockets with identical dimension of 220 mm × 200 mm. It is important to note that the vertical lengths of the slab type I, 1,980 mm for the left and 1,956 mm for the right, are different so that the slab is in the shape of a trapezoid. It is also noted that the shear pocket plays a role in assembling precast slabs with precast girders. For the precast slab type II, the dimensions are 12,600 mm × 2,480 mm × 240 mm and it has 25 shear pockets with identical dimension of 440 mm × 140 mm. It is important to note that the corners of the slab have two different angles (89.4° and 90.6°) such that the slab is in the shape of a parallelogram. In other words, both the slabs are a non-rectangular shape of precast slab. In the blueprint, the dimensional tolerances are specified. For the length and the width of the two precast slabs, the tolerances are specified as ± 10 mm and ± 5 mm, respectively. For the dimensions (length and width) and the position of the shear pockets, the tolerances are specified as ± 5 mm. Hence, the certain objective of the field test was to identify whether the dimensional properties of the precast slabs and the shear pockets conform to the corresponding tolerances - specifically, to estimate 1) the dimension errors of the precast slab and the shear pockets and 2) the position errors of the shear pockets on the precast slab. Here, the position of the shear pocket is defined as the distance between the center point of a shear pocket and the closest edge of the precast slab.
Table 6.1 Specifications of the tested scan parameter and precast slab

<table>
<thead>
<tr>
<th>Aspect</th>
<th>Property</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scan parameter</td>
<td>Scan distance</td>
<td>9 m</td>
</tr>
<tr>
<td></td>
<td>Angular resolution</td>
<td>0.018, 0.036, 0.072°</td>
</tr>
<tr>
<td></td>
<td>Scan time</td>
<td>25 (0.018°), 8 (0.036°), 4(0.072°) min.</td>
</tr>
<tr>
<td>Precast slab</td>
<td>Dimension</td>
<td>Type I - 10,610 mm × 1,980 (1956) mm × 240 mm</td>
</tr>
<tr>
<td></td>
<td></td>
<td>220 mm × 200 mm for each shear pocket</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Type II – 12,600 mm × 2,480 mm × 240 mm</td>
</tr>
<tr>
<td></td>
<td></td>
<td>440 mm × 140 mm for each shear pocket</td>
</tr>
<tr>
<td></td>
<td>Specified tolerance</td>
<td>± 10 mm for precast slab length</td>
</tr>
<tr>
<td></td>
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<td>± 5 mm for precast slab width</td>
</tr>
<tr>
<td></td>
<td></td>
<td>± 5 mm for shear pocket dimension and position</td>
</tr>
</tbody>
</table>

### 6.2.2 Improved coordinate transformation algorithm

In this section, a new coordinate transformation algorithm developed for the filed test is discussed. Fig. 6.3 shows the range image of the full-scale precast slab type I. In the previous coordinate transformation algorithm described in Chapter 2.3.2, this process requires three points ‘near’ the corners of the precast slab. However, there is a difficulty in identifying three points because the range image generated from the point cloud data is distorted (curved) due to the large-scale dimension of the precast slab, and the scan points corresponding to external steel bars used for lifting are positioned near the corners of the precast slab. As a result, the coordinate transformation process is hard to be accurate and automated. To resolve this, a new coordinate transformation algorithm is developed using directly the 3D point cloud data instead of using the initial 2D range image. This algorithm consists of the following four steps.

**Step 1- Data cleansing:** Removal of unwanted scan points is first conducted using a threshold of Z coordinate. Since the laser scanner is assumed to be positioned right above the center of the precast slab, the Z values of the point cloud within the precast slab are always larger than those of the unwanted background scan points as shown in Fig. 6.4 (a). Based on this knowledge, a threshold value is determined to filter out the useless scan points. The threshold is set as follows. First, $Z_{\text{max}}$, which is the maximum Z coordinate of all the scan points, is selected. Then, $Z_{\text{mid}}$, which is the Z coordinate corresponding to the point whose X and Y coordinates are the median value of all the points, is estimated from a linear interpolation based on all the
Chapter 6. Application to Full-scale Precast Concrete Elements

points. Here, denote the distance difference between $Z_{\text{max}}$ and $Z_{\text{mid}}$ as $d$. Since the scanned surface is assumed to be planar, the minimum Z coordinate of all the valid points, $Z_{\text{min}}$, would also have a difference of $d$ from $Z_{\text{mid}}$. As a result, $Z_{\text{min}}$ is ideally equal to $Z_{\text{mid}} - d$. To determine a threshold for data cleansing, another $d$ is applied as a safety factor and the threshold $T$ is set as $Z_{\text{mid}} - 2d$. All the points that have a Z coordinate smaller than $T$ are regarded as the background points and then removed as shown in Fig. 6.4 (b).

![Figure 6.3 The range image of precast slab type I](image)

![Figure 6.4 Removal of background scan points: (a) Selection of a threshold for data cleansing; (b) Data cleansing result](image)
Step 2 – Four corner pixel extraction of a range image: Once unwanted scan points are eliminated, a range image is generated from the remained scan data, and four corner pixels of the range image corresponding to the four corner of the precast slab are extracted. Fig 6.5 shows the four sub-steps for this process. First, a range image is generated by constructing virtual grids along the X and Y axes and dividing the X-Y plane into user-defined pixels. For each pixel, a group of X, Y and Z values are allocated. X and Y values of each pixel are the coordinates of its center while Z value is generated from the linear interpolation based on remaining scan data. Note that if a pixel is inside the slab’s boundary, a valid Z value is returned from the interpolation. But, if a pixel is outside the slab’s boundary, no values of Z coordinate are given to the pixel. For each pixel with a valid Z value, the range is computed by the formula $\sqrt{X^2 + Y^2 + Z^2}$, then normalized to the range of $[0, 1]$. Here, the range values ‘0’ and ‘1’ denote the ‘black’ and ‘white’ colors in the range image. As shown in Fig. 6.5 (a), the precast slab closer to the laser scanner is shown in a darker grey while the background behind the slab is shown in a lighter grey. Second, the edge of the precast slab is then extracted. In this study, a customized edge detector was developed so that only the outside boundary edges of the precast slab are extracted as shown in Fig. 6.5 (b). The edge detector finds only the first and last pixels that have a range value less than 1 in each row and column of the range image, and they are marked as edge pixels. Third, four line segments which represent the four sides of the slab are detected using the Hough Transform as shown in Fig. 6.5 (c). Finally, four corners A, B, C and D of the slab are extracted by finding the intersection points of the four line segments as shown in Fig. 6.5 (d), and the 3D coordinates of the four corner pixels are extracted.
Chapter 6. Application to Full-scale Precast Concrete Elements

Figure 6.6 Finding of an ideal left-side direction of the slab for coordinate transformation: (a) Ideal coordinate system; (b) Example of an abnormal slab with a manufacturing error (red dotted line); (c) Coordinate transformation result with a biased left-side direction AD of the slab; (d) Finding of an ideal left-side direction AD by best matching

Step 3 – Finding of an ideal left-side direction of the slab: Once the corners’ coordinates are extracted, a correction is undertaken to ensure that the coordinate system constructed by the corners is in accordance with the desired coordinate system. In the ideal coordinate system as shown in Fig. 6.6 (a), the left-bottom corner is the origin and the left side of the slab is along the Y axis. Note that the investigated slab in this study is a trapezoid (non-rectangular) slab, and the as-built and as-design sides of the slab are shown in red and blue lines, respectively. However, there is a possibility that the as-built left-side of the precast slab, which is constructed by corner A and D, is a little inclined due to a manufacturing error as shown in Fig. 6.6 (b). In this case, if the tilted left side is taken as the Y-axis, the scan data after coordinate transformation would be like what is shown in Fig. 6.6 (c). Obviously, with a biased left-side direction AD of the slab, the scan data after coordinate transformation doesn’t match the as-design one which is in the ideal coordinate system. Hence, a correction algorithm that makes as-built scan points after coordinate transformation matches the as-design one is developed. Fig. 6.7 shows the pseudo code of the correction algorithm for the coordinate transformation. This algorithm finds the ideal left-side direction AD of the slab. To do this, a set of directions is first taken.
Chapter 6. Application to Full-scale Precast Concrete Elements

<table>
<thead>
<tr>
<th>Input: as-design corners ((A_0, B_0, C_0, D_0)), as-built corners ((A, B, C, D))</th>
<th>Output: ideal left-side direction AD (idealY)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 generate a set of directions as candidates of ideal left-side direction AD (DrctSet);</td>
<td></td>
</tr>
<tr>
<td>Initialization</td>
<td></td>
</tr>
<tr>
<td>2 idealY = direction of AD;</td>
<td></td>
</tr>
<tr>
<td>3 minError = ((D_{AA_0}^2 + D_{BB_0}^2 + D_{CC_0}^2 + D_{DD_0}^2) / 4);</td>
<td></td>
</tr>
<tr>
<td>Iterative Search</td>
<td></td>
</tr>
<tr>
<td>4 for each direction in DrctSet</td>
<td></td>
</tr>
<tr>
<td>5 take this direction as Y axis and conduct coordinate transformation;</td>
<td></td>
</tr>
<tr>
<td>6 get corners after transformation: (A_1, B_1, C_1, D_1);</td>
<td></td>
</tr>
<tr>
<td>7 thisError = ((D_{A_1A_0}^2 + D_{B_1B_0}^2 + D_{C_1C_0}^2 + D_{D_1D_0}^2) / 4);</td>
<td></td>
</tr>
<tr>
<td>8 if thisError &lt; minError</td>
<td></td>
</tr>
<tr>
<td>9 minError = thisError;</td>
<td></td>
</tr>
<tr>
<td>10 idealY = this direction;</td>
<td></td>
</tr>
<tr>
<td>11 end</td>
<td></td>
</tr>
<tr>
<td>12 end</td>
<td></td>
</tr>
</tbody>
</table>

**Figure 6.7** Pseudo code for finding the ideal left-side direction AD of the slab

as candidates of the ideal left-side direction AD. These directions are generated from a dense linear sampling within the range of ‘direction of AD ± \(\varepsilon\)’. Here, \(\varepsilon\) is determined as the largest angle among the angles between four pairs of the slab sides, i.e. angle between side AB and \(A_0B_0\), between side BC and \(B_0C_0\), etc. For each candidate direction of AD, coordinate transformation is conducted by taking this candidate as the Y-axis, and the mean square of the distances between the four pairs of corners, i.e. distance between point \(A_1\) and \(A_0\), between point \(B_1\) and \(B_0\), etc., is calculated. The ideal left-side direction AD of the slab with respect to the as-design side is found when the mean square of distances is minimized as shown in Fig. 6.6 (d).

Step 4 – Coordinate transformation: Once the extraction of the ideal corners (\(A_1, B_1, C_1\) and \(D_1\)) is completed, corner \(D_1\) is adjusted to \(D_2\) on the Y axis and corner \(B_1\) is also adjusted to \(B_2\) on the X axis so that it makes up a rectangular coordinate system. Finally, the scan points in the scanner coordinate system are transformed into the object coordinate system by taking corner A as the origin and \(AB_2\) and \(AD_2\) as the X and Y axes.
6.2.3 Improved edge and corner extraction algorithm

In the field test, there were other technical challenges encountered during the data analysis, which are associated with edge and corner extractions. First, as can be seen in Fig. 6.8, the side and middle areas of the slab have different incident angles due to the long size of the slab. For instance, the incidence angle of the edges (sides) of the precast slab from the laser scanner was measured at approximately 25°, while the incidence angle of the inner shear pockets near the center of the slab was about 10°, resulting in poor edge extraction results on the surface area near the edges. Note that the negative effect of a large incident angle on the dimensional estimation results and its causes are explained in Chapter 2.4.2. Second, external barriers, i.e. steel bars, were positioned near vertical edges of the precast slab, which prevent extractions of accurate edge points. Fig. 6.9 (a) shows a photo of the steel bars built for lifting the precast slab. Note that the exterior barriers does not included in the blueprint of the precast slab. It can be seen in Fig. 6.9 (b) that the scan points of the steel bars are still remained after the implementation of the edge point extraction, which may affect negatively the dimension and position estimation for the precast slab.

![Figure 6.8 Varying incident angle according to different positions of the precast slab](image-url)
Chapter 6. Application to Full-scale Precast Concrete Elements

Figure 6.9 Effect of external attachments on edge extractions: (a) A photo of steel bar for lifting; (b) The edge extraction result containing scan points of the steel bars

Figure 6.10 Near-field non-edge point removal based on the RANSAC algorithm

In order to deal with these problems, a two-step non-edge point elimination algorithm is proposed. As the first step, the far-field non-edge point removal algorithm, which is illustrated in Fig. 2.9 of Chapter 2.3.3, is executed after the initial edge point extraction. Note that the far-field non-edge point removal algorithm is based on the observation that the non-edge points are sparsely scattered from the edges while the edge points are densely aligned along the edge with equal spacing. However, this far-field non-edge point removal algorithm is not effective in removing non-edge points near edge lines. To improve the edge extraction accuracy, the RANSAC (RANdom Sample Consensus) algorithm (Fischler and Bolles 1981) was employed to the remaining edge candidate points after implementing the first step of eliminating the non-edge points. Note that the RANSAC algorithm is an iterative method to estimate the parameters with a high degree of accuracy even when a significant number of outliers are present in the data set. Fig. 6.10 shows the performance results of the RANSAC algorithm. It can be seen that the fitted two lines are a little biased due to the remaining non-edge scan points in Fig. 6.10(a), but more accurate line fittings are obtained from the employment of the RANSAC algorithm in Fig. 6.10(b), resulting in more accurate and reliable dimensional estimation results.
6.2.4 Field test results

Figure 6.11 Data processing results of the precast slab type I

Fig. 6.11 shows the data processing results of the precast slab type I from the field test. Note that the results were obtained from the case of angular resolution of 0.036°. Once the point cloud of the precast slab was acquired with the laser scanner (step 1), coordinate transformation based on the algorithm described in the previous section was implemented (step 2). Subsequently, edge points were obtained from the two-step non-edge point removal algorithm and the corners were extracted from the intersection of the fitted edge lines (step 3). Finally, the dimensions and positions of the precast slab and shear pockets were computed using the extracted corners and the dimensional compensation model.

Using the extracted corner points, dimensions and positions of the precast slab and shear pockets are calculated. Fig. 6.12 shows the dimensional errors in the case of angular resolution of 0.036° by comparing the estimated ones with the design dimensions of the blueprint. In contrast with the dimension error results, the position estimation error of some shear pockets are significantly large. For instance, the horizontal position error of #5 shear pocket exceed 40 mm and the vertical position errors of #4, #8 and #15 are over 15 mm. Table 6.2 summarizes the dimension and position estimation errors compared with the blueprint under varying angular resolutions. For the dimension error estimation, a total of 68 dimensions, i.e. 4 for the slab and 64 for the sixteen shear pockets, were estimated from each scan. The average dimension errors of 4.4, 4.6 and 4.8 mm were obtained for the angular resolutions of 0.072, 0.036 and 0.018°, respectively. For the position error estimation, a total
of 32 position errors were obtained from each scan, and the average position errors of 9.4, 7.2, 7.4 mm were obtained for each angular resolution such that all the scan cases over the allowable tolerance of 5 mm.

To investigate whether the obtained large position errors are true, a manual inspection was carried out on the precast slab type I. Fig. 6.13 illustrates the dimensional results of the case of 0.036° angular resolution by comparing it with the manual inspection. It can be observed that the position errors of shear pockets of #4, #5, #8 and #15 are significantly reduced, indicating that the positions of the shear pockets were incorrectly manufactured. Table 6.3 summaries the dimension and position estimation errors compared to the manual inspection. It can be seen that the dimensional errors for all scan cases are within the specified tolerance of 5 mm except for the case of 0.072° angular resolution, demonstrating that the proposed DQA technique assesses dimensional checklists of full-scale precast concrete elements in a robust and accurate manner.

**Figure 6.12** Dimensional estimation results compared with blueprint for precast slab type I: (a) dimension; (b) position

**Figure 6.13** Dimensional estimation results compared with manual measurement for precast slab type I: (a) dimension; (b) position
For precast slab type II, Fig. 6.14 shows the dimensional errors in the case of angular resolution of 0.036° by comparing the estimated ones with the blueprint dimensions. In contrast with the dimension error result, the position estimation error of some shear pockets are significantly larger, especially in the horizontal position. Table 6.4 summaries the dimension and position estimation errors compared with the blueprint of the precast slab type II under varying angular resolutions. For the dimension error estimation, a total of 104 dimensions, i.e. 4 for the slab and 100 for the 25 shear pockets, were estimated from each scan. The average dimension errors of 5.3, 3.3 and 3.6 mm are obtained for the angular resolutions of 0.072, 0.036 and 0.018°, respectively. For the position error estimation, a total of 50 position errors were obtained from each scan, and the average position errors
of 9.2, 7.7, 5.4 mm are obtained for each angular resolution such that all the scan cases are over the allowable tolerance of 5 mm.

In order to investigate whether the obtained large position errors are true, a manual inspection was carried out on the precast slab type II. Fig. 6.15 illustrates the dimensional results of the case of angular resolution of 0.036° by comparing with the manual inspection. It can be observed that the position errors of shear pockets are significantly reduced, indicating that the positions of the shear pockets were incorrectly manufactured. Table 6.5 summarizes the dimension and position estimation errors compared to the manual inspection. It can be seen that the dimensional errors for all scan cases are within the specified tolerance of 5 mm except for the case of angular resolution of 0.072°, demonstrating that the proposed DQA technique assesses dimensional checklists of full-scale precast concrete elements in a robust and accurate manner.

**Figure 6.14** Dimensional estimation results compared with blueprint for precast slab type II: (a) Dimension; (b) Position

**Figure 6.15** Dimensional estimation results compared with manual measurement for precast slab type II: (a) Dimension; (b) Position
Table 6.4 Dimensional estimation results compared with the blueprint for precast slab type II

<table>
<thead>
<tr>
<th>Angular resolution (°)</th>
<th>Dimension error (mm)</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Length (slab)</td>
<td>Width (slab)</td>
<td>Length (shear pocket)</td>
<td>Width (shear pocket)</td>
<td>Ave.</td>
</tr>
<tr>
<td>0.072</td>
<td>4.2</td>
<td>5.8</td>
<td>4.7</td>
<td>5.5</td>
<td>5.3</td>
</tr>
<tr>
<td>0.036</td>
<td>8.4</td>
<td>6.2</td>
<td>2.3</td>
<td>3.7</td>
<td>3.3</td>
</tr>
<tr>
<td>0.018</td>
<td>5.6</td>
<td>6.9</td>
<td>2.0</td>
<td>4.7</td>
<td>3.6</td>
</tr>
</tbody>
</table>

Table 6.5 Dimensional estimation results compared with manual measurement for precast slab type II

<table>
<thead>
<tr>
<th>Angular resolution (°)</th>
<th>Dimension error (mm)</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Length (slab)</td>
<td>Width (slab)</td>
<td>Length (shear pocket)</td>
<td>Width (shear pocket)</td>
<td>Ave.</td>
</tr>
<tr>
<td>0.072</td>
<td>5.8</td>
<td>6.2</td>
<td>4.0</td>
<td>7.0</td>
<td>5.7</td>
</tr>
<tr>
<td>0.036</td>
<td>0.9</td>
<td>3.6</td>
<td>3.5</td>
<td>4.3</td>
<td>3.4</td>
</tr>
<tr>
<td>0.018</td>
<td>1.0</td>
<td>4.7</td>
<td>4.0</td>
<td>3.2</td>
<td>3.6</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Angular resolution (°)</th>
<th>Position error (mm)</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Length (shear pocket)</td>
<td>Width (shear pocket)</td>
<td>Ave.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.072</td>
<td>6.4</td>
<td>4.0</td>
<td>5.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.036</td>
<td>4.7</td>
<td>1.5</td>
<td>3.1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.018</td>
<td>3.2</td>
<td>2.5</td>
<td>2.8</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

To further investigate the dimensional estimation accuracy of the proposed DQA technique, a comparison test with a commercialized DQA technique, i.e. deviation analysis, was conducted in this study. Note that the deviation analysis is a method of measuring the dimensional discrepancies between the design model and an as-built model generated from the point clouds of several scans. Fig. 6.16 shows the deviation analysis results of tested precast slab type I. For the deviation analysis, point clouds of 10 different position scans were used to create a 3D as-built model. In addition, commercial software, Cyclone (Leica Geosystems. 2014) and Geomagic Studio (Geomagic Inc. 2014), were used for registration of the point clouds and estimation of the dimension discrepancies between two models.
of the precast slab. The different colors presented in Fig. 6.16 indicate the varying dimensional deviation levels. Table 6.6 summarizes the accuracy comparison results between the proposed DQA technique and the deviation analysis. It is reported that the proposed DQA technique results in more accurate dimensional estimation performance (3.2 mm) than that (9.4 mm) of the deviation analysis, proving that the proposed DQA technique can provide a robust and accurate capability for dimensional estimations of full-scale precast concrete elements.

![Figure 6.16 Deviation analysis between the design model and as-built model of precast slab type I](image)

**Table 6.6** Dimensional estimation comparison with conventional deviation analysis for precast slab type I

<table>
<thead>
<tr>
<th>Method</th>
<th>Dimension error (mm)</th>
<th>Position error (mm)</th>
<th>Ave.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Length (Slab)</td>
<td>Width (Slab)</td>
<td>Length (S. P.)</td>
</tr>
<tr>
<td>Deviation Analysis</td>
<td>20.0</td>
<td>4.5</td>
<td>1.8</td>
</tr>
<tr>
<td>Proposed DQA technique</td>
<td>2.0</td>
<td>5.7</td>
<td>3.4</td>
</tr>
</tbody>
</table>

*S.P. denote the ‘shear pocket’.

**Table 6.7** Comparison of time required for the DQA of precast slab type I among three different methods

<table>
<thead>
<tr>
<th>Time (minutes)</th>
<th>Scanning</th>
<th>Modeling</th>
<th>Measuring</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deviation analysis</td>
<td>30 (3 each scan) * 10 (position)</td>
<td>60</td>
<td>10</td>
<td>100</td>
</tr>
<tr>
<td>Manual inspection</td>
<td>-</td>
<td>-</td>
<td>90</td>
<td>90</td>
</tr>
<tr>
<td>Proposed technique</td>
<td>5</td>
<td>-</td>
<td>0.5</td>
<td>5.5</td>
</tr>
</tbody>
</table>
6.3 Cloud-BIM based Inspection Data Storage and Management

6.3.1 Introduction of loud-BIM for QA of precast concrete element

Commercial BIM solutions, such as Autodesk Revit and Bentley Architecture, have ‘stand-alone’ system framework and are developed specifically for visualizing project information (Chuang et al. 2011). However, this nature of BIM solutions makes it difficult for participants from different sites to access and update a common set of information, resulting in issues with communication and information distribution. As an alternative, cloud-computing technology has gained much attention in the BIM sector for its unique advantages when applied to management of BIM data. The most common meaning of ‘cloud computing’ refers to the delivery of hosted IT services over the Internet (Whatis.com 2009), so users can access these services without previous knowledge of managing the required computing resources. Because of this unique feature, the cloud-BIM concept can change the form of BIM computing framework from “stand-alone” to “host-based”. In addition, the cloud-BIM concept offers many benefits, as it is economical, flexible and scalable. First, operating costs can be significantly reduced, since virtualized servers and software built in a cloud-BIM require no physical space to setup and is provided by ‘pay-as-you-go’ services. Second, the cloud-BIM concept allows for more flexibility amongst the members of a project both in and out of the workplace, because they can assess and share documents over the Internet almost anywhere. Third, the cloud-BIM concept offers scalability because a project team can upscale and downscale IT requirements as needed.

Current data storage and delivery for QA of precast concrete elements is conducted based on the following procedure (Yin et al. 2009): (1) certified inspection personnel monitor and record the inspection results of specified checklists in the inspection form; and (2) once the QA is completed, the inspector comes to the office and stores the inspection data of the inspection form in a database system via a computer. The current data storage and delivery system, however, is inefficient due to the duplicated process of recording the inspection data in both document and database forms. Moreover, there is a possibility of data entry error and inspection form loss, as well as difficulties in interactively updating and sharing the inspection data with other project participants who work in different places.

To overcome the limitations of the current data storage and delivery mechanism for QA of precast concrete elements, a cloud-BIM system is proposed for effective and flexible data storage and management of precast concrete QA. In terms of efficiency in data storage and delivery, the proposed cloud-BIM system provides efficiency and flexibility over the current method. Therefore, it is expected that the proposed cloud-BIM system adapting hosted IT services over the Internet has potential as an efficient and effective data storage and delivery for QA of precast concrete elements.
6.3.2 System architecture of the proposed cloud-BIM

![System architecture of the proposed cloud-BIM based data storage and management for precast concrete QA](image)

Figure 6.17 System architecture of the proposed cloud-BIM based data storage and management for precast concrete QA

Fig. 6.17 shows the system architecture of the proposed cloud-BIM based data storage and management system for QA of precast concrete elements. In the system, three different parties (precast supplier, inspector and construction engineer) are involved and designed for each party to connect the cloud-BIM system through a master node. Here, the master node serves as a gateway like web-browsers to the cloud-BIM system and do not store any QA data itself. Through the master node, users from all three parties generate queries regarding the QA of precast concrete elements, which the workers in the cloud-BIM execute. There are two workers in the cloud-BIM, which are namely ‘computing’ and ‘storage’ modules. In the computing model, once the automated data matching process between the BIM model and the inspected QA data is complete, the IFC files are updated based on the calculated discrepancy of QA data is performed. On the other hand, the storage module can be regarded as the BIM server, which serves as a repository for data during a construction project, including the BIM model of precast concrete elements and its updated IFC files.

The overall precast concrete QA data flow in the proposed cloud-BIM system can be described as follows: (1) Precast element suppliers upload detailed information about the elements in the cloud-BIM in the form of IFC after manufacture; (2) At the inspection site, inspectors obtain the QA results of the precast elements after scanning and upload them into the cloud-BIM system. Here,
data type of the QA data is assumed to be a format familiar to inspectors; (3) In the computing module, data matching process between the design BIM model stored in the storage module and the uploaded QA data is carried out and the discrepancies are obtained and reflected on the updated IFC file; (4) The decision of whether the inspected precast concrete element is acceptable or not is made by comparing the discrepancy with the corresponding tolerances of the QA checklists in the computing module; and (5) Finally, the accepted elements are delivered to the construction sites and construction engineers assess the QA data via portable devices as needed with the aim of precise connection of the accepted precast concrete elements.

6.3.3 Data matching method

In order to automatically conduct the decision-making of the precast element acceptance, a data matching process that automatically extracts the required geometry information from the BIM model and matches with the QA data is necessary. In this study, a data matching method, which is undertaken in the computing module of the cloud-BIM system, is developed as shown in Fig. 6.18. In this study, it is assumed that the dimensional (dimensions and positions) QA outcomes are stored in a

![Figure 6.18 Data matching method between the QA results and the design BIM model for precast slab I](image-url)
template of CSV (Comma-Separated Values) file, and then uploaded into the cloud-BIM by the inspectors. The design BIM model stored in IFC format stored in the BIM library is called up from the computing module and an IFC parser is used to read and extract the IFC file associated with the geometry data to be matched with the inspection results.

In an IFC file, elements of a structure are expressed by IFC entities which have a hierarchical structure. For example, the IFC data representing a precast slab with several rectangle holes (shear pockets) contains higher or lower level entities expressing specific information of the precast slab as shown in Fig. 6.18. The IFC entity representing the geometry information of the precast slab is IfcExtrudedAreaSolid (#298), meaning the 3D object created by extruding a cross section with a sweeping direction. Here, the cross section stands for the horizontal cross section of the precast slab model and the sweeping direction is the height direction perpendicular to the cross section. The cross section is expressed with IfcArbitraryProfileDefWithVoids (#293), which means the two-dimensional profiles of the closed holes. In this IFC model, the profile has two types of boundaries: (1) an outer boundary which represents the outer edge of the precast slab; and (2) inner boundaries representing the holes (shear pockets) within the slab. The outer boundary is expressed with IfcPolyline (#131) and it contains the coordinate information of four corner points expressed with IfcCartesianPoint (#123, #125, #127 and #129), and these four points are the corner points of the precast slab’s cross section to be used for the data matching. In a similar manner, the inner boundaries are also expressed with IfcPolyline (#141, #151…#291) and they are extracted for the data matching of dimensional properties of the shear pockets. After extracting the desirable geometry information from the BIM model based on the proposed data matching method, discrepancies of the dimensional QA data between the BIM model and the inspected data is computed automatically and the decision on whether the inspected precast element is acceptable or not is made based on the comparison results between the discrepancies and the corresponding tolerances.
6.3.4 Extension of IFC file for the inspection QA data

Table 6.8 Properties of the proposed IFC property set “QualityAssessment”

<table>
<thead>
<tr>
<th>Property Name</th>
<th>Data Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Checklists</td>
<td>String</td>
<td>Inspection checklists</td>
</tr>
<tr>
<td>Tolerance_Dimension</td>
<td>double</td>
<td>Allowable tolerance of precast slab dimension</td>
</tr>
<tr>
<td>Tolerance_Position</td>
<td>double</td>
<td>Allowable tolerance of shear pocket position</td>
</tr>
<tr>
<td>Discrepancy_Dimension</td>
<td>double</td>
<td>Dimension difference obtained from data matching</td>
</tr>
<tr>
<td>Discrepancy_Position</td>
<td>double</td>
<td>Position difference from data matching</td>
</tr>
<tr>
<td>IsAccepted</td>
<td>boolean</td>
<td>Whether the precast slab is accepted or not</td>
</tr>
</tbody>
</table>

Since the latest version of IFC schema (IFC 2x4) currently does not include information regarding QA of precast concrete elements, an IFC extension containing a new property set and its properties was proposed in this study to store the quality assessment information in IFC files. The proposed property set is named ‘QualityAssessment’. As shown in Table 6.8, the property set consists of six properties – QA checklists, dimensional tolerances, dimensional discrepancy and boolean-type decision making result. The dimensional tolerances are defined as the allowable tolerances for each checklist and these values are normally pre-determined prior to the launch of a construction project. The dimensional discrepancy is the outputs of the data matching process discussed in the previous section. The ‘IsAccepted’ property represents the decision of whether the inspected precast element is accepted or not. In the IFC extension, an IFC parser executing the storing and retrieving of the QA data of precast concrete elements was used to extend the proposed property set in IFC files.

6.3.5 Data matching and IFC extension result

Fig. 6.19 shows the data matching results between the BIM models and the as-built models of both the precast slabs. The dimensional discrepancy is expressed by different colors based on the distance between two groups of corner points. Note that the as-design boundary is drawn in blue and the as-built boundary is drawn in red. The color filled between the as-design and as-built boundaries
indicates how large the discrepancy is. For instance, the position error of #5 shear pocket is represented in dark red, which means the discrepancy is over 40 mm. Fig. 6.20 shows the IFC extension results that the new property set and its properties are shown in an IFC viewer, FZKViewer (KIT 2014). The dimensional quality data of the precast slab type I including the dimensional tolerance, actual dimensional discrepancy and acceptance decision are correctly stored and updated in the IFC file.

Figure 6.19 Data matching result between as-design and as-built geometries for both precast slab type I & II
Chapter 6. Application to Full-scale Precast Concrete Elements

A commercial cloud server, Amazon Elastic Compute Cloud (EC2) (Amazon, 2014), was used in this study to validate the feasibility of the proposed cloud-BIM system. Two instances (workers), i.e. the computing and storage modules, were created in the cloud server. In the two instances, the data matching process and storing and updating the IFC files were implemented, respectively. For the implementation of the data matching process, an IFC parser, JSDAI (JSDAI 2014) which can read and write IFC schema, was utilized to extract the necessary geometric data of the BIM model. For the storage of dimensional quality data, MySQL (ORACLE Inc. 2014) which is an open-source relational database management software, was used as the BIM server. Note that the two instances are connected each other so that storing and updating the dimensional quality data can be conducted automatically whenever queries are requested. Fig. 6.21 shows the developed user interface of the cloud-BIM system. Among the four sub-menus (‘login’, ‘upload’, ‘inspection_result’ and ‘update_IFC’) of the user interface, the ‘inspection_result’ menu is shown as an example. When a model ID is provided, the quality inspection results are dynamically presented when they are called up from the storage module of the cloud-BIM system.

Figure 6.20 Property set and its properties for precast concrete QA shown in IFC viewer
Chapter 6. Application to Full-scale Precast Concrete Elements

Figure 6.21 Screen-shot of the user interface of the cloud-BIM system for precast concrete QA

6.4 Chapter Summary

This chapter investigates the feasibility of the proposed methods for QA of precast concrete elements. There are two main objectives of this chapter, which are 1) the application of the developed dimensional QA technique to full-scale precast concrete elements with complex geometries; and 2) the validation of the proposed data storage and management method of the precast concrete element QA through a cloud-BIM system which is regarded as a potential means of data storage and management. To this end, full-scale precast slabs were used as test targets to validate the effectiveness of the dimensional QA technique in a precast manufacturing company. The challenges encountered during the data analysis of the full-scale test were investigated and resolved using optimized algorithms. Furthermore, comparison of measurement accuracy between the conventional deviation analysis technique and the proposed DQA technique was conducted. From the comparison results, the average dimensional error of the proposed technique for precast slab I was 3.2 mm, while that of the conventional deviation analysis was 9.4 mm, demonstrating that the proposed technique has potential in estimating and assessing the dimensional properties of the precast concrete element. Furthermore, the proposed cloud-BIM system for effective QA data storage and management was successfully validated.
Chapter 7. Conclusion

7 CONCLUSION

7.1 Summary of the Work

This study explores intelligent precast concrete quality assessment (QA) system and it’s technique based on 3D laser scanning and building information modeling (BIM) technology. The specific objectives of this dissertation are (1) the development of a new dimensional and surface QA technique, (2) the development of a BIM-based data storage and management framework for precast concrete QA (3) scan parameter optimization of the dimensional QA technique for accurate precast concrete QA and (4) validation through field tests for real applications.

Objective (1)

Dimensional and surface QA techniques have been successfully developed. First, a new dimensional assessment technique that automatically assesses the dimensional qualities of precast concrete elements whether the dimensional quality is within the tolerances have been developed using a 3D laser scanner. A robust edge extraction algorithm, which is able to extract only the scan points within the edges of a target precast concrete element, is developed based on the unique spatial alignment of scan points captured from the laser scanner. Experimental tests on a lab scale specimen as well as lab scale actual precast concrete elements have been performed to validate the effectiveness of the proposed dimensional QA technique. Second, a new surface QA technique that simultaneously localizes and quantifies surface defects of precast concrete surfaces has been developed. For the surface QA technique, two defect sensitive features with complementary properties, have been extracted and combined for improved localization and quantification of surface defects. A defect classifier has been also developed to automatically diagnose whether the investigated surface region is damaged, where the defect is located, and how large it is. Numerical simulations and experiments have been conducted for validation of the developed surface QA technique. The details of two QA techniques and its validation tests are described in Chapters 2 and 3, respectively.

Objective (2)

The BIM-based data storage and management framework for the QA of precast concrete elements has
been developed. The framework has been developed to answer four essential questions for precast concrete QAs, which are (1) what the QA checklists should be, (2) what QA procedure should be employed, (3) which kind of laser scanner is appropriate and which scan parameters are most appropriate for the intended specific QA, and (4) how the inspected QA data can be effectively stored and delivered. The proposed framework has focused on dimensional and surface QAs and the feasibility of the framework for dimensional and surface QAs of precast concrete elements have been investigated through case studies. The results of the case studies have been described in Chapter 4.

**Objective (3)**

Optimal scan parameter selection has been successfully conducted. The method of selecting optimal scan parameters of a laser scanner has been proposed in order to ensure that the developed dimensional QA technique provides satisfactory measurement accuracy regardless of scan parameters. A laser beam model that estimates the laser beam position of the laser scanner have been developed by constructing the geometric position of a laser beam and incorporating the measurement noise of the laser beam into the mathematical estimated position of the laser beam. The developed laser beam model has been successfully validated by comparing it with experiment data. The details of parametric studies based the developed model for finding optimal scan parameters have been described in Chapter 5.

**Objective (4)**

The applicability of the dimensional QA technique to full-scale precast slabs has been investigated. First, two types of full-scale precast concrete slabs with complex geometries have been scanned in a precast concrete factory and dimensional QA checklists including dimensions and positions have been inspected. For this filed test, new algorithms have been developed to tackle obstacles created by large-scale implementations. A comparison test with the conventional deviation analysis has been conducted and the robustness of the developed dimensional QA technique has been successfully demonstrated. Second, a cloud-BIM based web-service for effective storage and management of precast concrete QA data have been developed. The details of the field test results and the cloud-BIM platform have been described in Chapter 6.
7.2 Uniqueness of the Work

The unique contributions of this work are summarized as follows:

(1) Development of automated dimensional and surface quality assessment techniques

In contrast with the conventional manual inspection approaches for precast concrete quality assessment, automated and remote dimensional and surface quality assessment techniques specially developed for precast concrete elements provide fast non-contact measurement. New coordinate transformation and edge extraction algorithms are developed for automated and complete dimensional quality assessment, and unique defect sensitive features and a new recursive algorithm are developed for improved localization and quantification of surface defects. The developed complete and automated dimensional and surface quality assessment techniques significantly reduce the burdens of the conventional manual inspection.

(2) Development of the framework for systematic dimensional and surface quality assessment

The systematic quality inspection and assessment of precast concrete elements is challenging through conventional manual inspection in terms of time and cost. The developed framework for quality assessment of precast concrete elements overcomes these limitations by answering the essential questions raised during real application. This framework systematically illustrates how dimensional and surface quality assessment for precast concrete elements can be implemented and how the inspection data can be stored and managed by combining laser scanning and building information modeling technology, resulting in efficient and effective quality assessment.

(3) Field tests for real applications

The feasibility tests of the proposed dimensional quality assessment technique are carried out on full-scale precast slabs. The field test on two types of precast slabs with complex geometry is a unique opportunity given by the research project. Through the real and unique experiments, the feasibility of the proposed dimensional quality assessment technique is successfully investigated and practical issues of the proposed technique are found. Furthermore, a comparison test with the conventional deviation analysis demonstrates the robustness of the developed dimensional quality assessment technique. In addition, the feasibility of the cloud-BIM system is investigated via commercial cloud services.
7.3 Future Work

It is expected that applications of the proposed quality assessment techniques and its data management system will be successful in effecting rapid and precise construction in the precast concrete industry. However, there are still several issues in this research, which are topics for future research. Ongoing efforts are briefly summarized below.

(1) Improvement of applicability of the dimensional and surface QA techniques

The proposed dimensional and surface QA techniques are currently limited to precast concrete elements with a nearly rectangular-shape and a uniform thickness. To improve and validate the performance of the proposed techniques for real applications, further validations are still needed for other types of precast concrete elements with more complex geometries such as curved and diamond shapes. Moreover, the scope of this research for QA inspection of precast concrete elements was limited to dimensions, positions and squarenesses for dimensional QA and spalling defects for surface QA. Further investigation on other QA checklists such as flatness, warping and distortion is necessary.

In addition, the proposed dimensional and surface QA techniques are implemented on only the top surfaces of precast concrete elements. To make the proposed techniques to be promising solutions for QA of precast concrete elements, further validation of the techniques on the side parts of precast concrete elements is necessary.

(2) Reduction of implementation time of the QA techniques

Although the proposed dimensional and surface QA techniques require less implementation time than conventional methods - manual inspection and the deviation analysis, implementation time needs to be further reduced so the productivity of the precast concrete element QA is enhanced. To achieve this demand, the algorithms of the QA techniques should be improved in a way that those are implemented quickly, and code transformation from the current program language to C is necessary. Furthermore, algorithm comparison with Point Cloud Library (PCL) will be conducted to investigate the difference of algorithm performances and implementation times.
(3) Improvement of the QA data management system

Implementation of the proposed QA data storage and delivery system for field tests was performed using a cloud server with a low-capacity, since this study focuses on the QA data of precast concrete elements and uses only two types of precast slabs. However, since the proposed QA data storage and delivery system operates based on all kinds of information of precast concrete elements and there are various types of precast concrete elements in real situations, an appropriate-capacity cloud server which accounts for these factors should be selected and used. In addition, it seems that the proposed IFC-file based scheme for precast concrete element QA requires large data capacity due to the voluminous IFC schema, so more efficient and effective means of QA data storage and management instead of IFC format needs to be considered. Lastly, the proposed cloud-BIM system should be realized in a prototype by improving the contents of the web-service.
Chapter 7. Conclusion
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레이저 스캐닝 및 빌딩 정보 모델링을 활용한 비접촉식 프리캐스트 콘크리트부재 품질평가

최근 교량 및 빌딩 건설에 있어서 공기단축 및 비용절감을 이유로 프리캐스트 콘크리트부재의 수요가 늘어나고 있다. 프리캐스트 부재 기반의 급속, 정밀 시공을 위해 부재의 품질검사가 필수적으로 수행되고 있지만, 현재의 품질검사는 대부분 인력에 의존하고 있어 시간 및 비용이 많이 소요되고 있다. 또한 건설 데이터의 저장 및 관리에 있어, 최근 빌딩 정보 모델링(BIM) 기술이 데이터의 저장성 관리에 목적으로 건설산업 전반에 보급화되기 시작하면서 프리캐스트 콘크리트 부재의 품질관리에 BIM 기반의 품질검사 기법의 필요성이 요구되고 있다. 이에 본 논문에서는 프리캐스트 콘크리트부재의 품질관리에 대한 품질검사 시스템을 개발하였다. 본 논문에서는 다음의 네 가지 목표를 위해 연구를 수행하였다: (1) 기반 및 표면결함 검사기법 개발, (2) 레이저 스캐닝 및 BIM 기반의 품질관리 체계(framework) 개발, (3) 향상된 품질검사를 위한 스크린 파라미터 최적화, (4) 실 프리캐스트 부재에 대한 적용성 검토.

첫째, 프리캐스트 콘크리트부재 품질적 및 사양별적인 검사기법을 개발하였다. 먼저 3차원 (3D) 검사기법은 레이저 스캔 데이터로부터 자동화된 검사 자동화를 위해 좌표변환 알고리즘 및 가장자리 점(edge-scan points) 만을 추출하는 벡터 합(vector-sum) 알고리즘을 개발하였고, 레이저 스캐나의 저항의 하위 데이터에 의해 불가피하게 발생하는 모서리(edge)의 산출물을 보상하기 위해 모서리 자동 산출 보상 알고리즘을 개발하여 치수 품질검사의 정확성을 높였다. 개발된 치수 검사기법의 검증을 위해 다양한 실험 규모의 실험을 수행하였다. 다음으로, 프리캐스트 콘크리트부재의 표면결함(surface defect) 검사기법을 개발하였다. 표면결함의 위치 및 손상 정도를 정량적으로 검사하기 위하여 계측된 3차원 계측정보에서 표면결함에 민감한 특징(feature) 정보들을 추출하였으며, 검사의 정확도 향상을 위해 추출된 각 특징정보를 융합하여 지수화한 융합 검사기법을 개발하였다. 또한 개발된 표면결함 검사기법의 자동화를 위하여 확률론적 표면결함 분류기(defect classifier)를 개발하였다. 개발된 표면결함 검사기법의 검증을 위하여 시뮬레이션 및 실험 규모의 실험을 수행하였으며, 손상크기 및 깊이가 2 mm 이상의 표면손상에 대하여 그 손상위치와 손상정도를 정확하게 검증할 수 있음을 알 수 있었다.

둘째, 레이저 스캐닝 및 BIM 기반의 지능형 품질관리 체계를 개발하였다. 개발된 프리캐스트 콘크리트 부재 품질관리 체계는 부재의 세조 후부터 공사현장 반출 시까지 품질관리에 있어서 필수적으로 요구되는 네 가지 사항에 대한 해결책을 제시하고자 하였다. 이
네 가지 사항은 다음과 같다: (1) 어떤 품질검사 항목을 검사해야 하는가? (2) 품질검사는 어떤 과정으로 수행되어야 하는가? (3) 각 품질검사 항목마다 어떤 레이저 스캐너를 이용하여 최적의 스캔 파라미터는 어떠한가? (4) 어떻게 품질검사 데이터를 체계적으로 관리하는가? 제안된 품질관리체계는 BIM과 연계되어 품질검사의 자동화 및 지능화가 가능하도록 하였다. 제안된 품질관리 체계의 검증을 위하여 사례연구(case study)를 진행하였으며 BIM과 연계한 제안된 체계의 적응 가능성을 확인하였다.

셋째, 프리캐스트 콘크리트 품질검사 기법의 신뢰성 향상을 위해 스캔 파라미터(scan parameter) 최적화 기법을 개발하였다. 개발된 치수 및 표면결함 검사 기술의 정확도는 계측 장비인 레이저 스캐너의 계측 파라미터에 의해 크게 영향을 받음으로 연구실 규모의 실험을 통해 알 수 있었는데, 계측 결과의 신뢰성을 높이기 위해 최적의 계측 파라미터 값을 찾는 것이 중요하다. 이를 위하여 본 논문에서는 레이저 광선(laser beam)의 기하학적 위치 정보 및 계측 오차를 산정하는 모델을 개발하였으며, 이 개발된 모델을 이용한 레이저 스캐닝 시뮬레이션을 통하여 치수 검사기법의 최적화된 계측 파라미터의 선정이 이루어졌다.

마지막으로, 본 연구에서는 개발된 품질 검사기법 및 시스템의 실 적용성을 검증하기 위해 현장시험을 수행 하였다. 길이 12 m의 복잡한 형상을 가진 두 종류의 실 프리캐스트 콘크리트 바닥판 부재를 대상으로 실험을 수행 하였으며, 성공적으로 개발된 치수 검사기법의 정확성 및 신뢰성을 입증하였다. 또한 기존 품질검사기법인 deviation analysis 와의 정확성 비교를 통해 개발된 품질 검사기법의 우수성을 확인하였다. 또한 실 부재로부터 계측된 품질검사 데이터의 체계적 관리를 위해 클라우드(cloud)-BIM 시스템을 제안하고 이 시스템을 상용 클라우드 서버에 구축하였다.

핵심어: 프리캐스트 콘크리트, 레이저 스캐닝, 빌딩 정보 모델링 (BIM), 품질 검사, 데이터 관리 시스템
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BOOK CHAPTER


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2009 – 2011  Online Continuous Monitoring of Bridge Structures: Smart Infra-Structure Technology Center, National Research Foundation of Korea (Funded: 140,000 USD for 03/01/07 to 02/28/11)

CONFERENCE PROCEEDINGS

International Conference


6. **Min Koo Kim**, Hoon Sohn, Chih-Chen Chang, “Active Dimensional Quality Assessment of Precast Concrete using 3D Laser Scanner,” ASCE International Workshop on Computing in Civil Engineering,
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**Domestic Conference**


