

BRIDGE STRUCTURAL INSPECTIONS USING BRIDGE INFORMATION MODELING (BrIM) AND UNMANNED AERIAL VEHICLES (UAVs)

by

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Sponsorship

Pacific Northwest Transportation Consortium

for

Pacific Northwest Transportation Consortium (PacTrans)
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University of Washington
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Seattle, WA 98195-2700

In cooperation with US Department of Transportation- Office of the Assistant Secretary for
Research and Technology (OST-R)



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Technical Report Documentation Page

| | | | |
|--|--|--|------------------------|
| 1. Report No. | 2. Government Accession No. 01701481 | 3. Recipient's Catalog No. | |
| 4. Title and Subtitle Bride Structural Inspections using Bridge Information Modeling (BrIM) and Unmanned Aerial Vehicles (UAVs) | | 5. Report Date 11/27/19 | |
| | | 6. Performing Organization Code | |
| 7. Author(s) Yelda Turkan, ORCID 0000-0002-3224-5462; Yiye Xu | | 8. Performing Organization Report No. 2017-S-OSU-2 | |
| 9. Performing Organization Name and Address PacTrans Pacific Northwest Transportation Consortium University Transportation Center for Region 10 University of Washington More Hall 112 Seattle, WA 98195-2700 | | 10. Work Unit No. (TRAIS) | |
| | | 11. Contract or Grant No. 69A3551747110 | |
| 12. Sponsoring Organization Name and Address United States of America Department of Transportation Research and Innovative Technology Administration | | 13. Type of Report and Period Covered Final Research | |
| | | 14. Sponsoring Agency Code | |
| 15. Supplementary Notes Report uploaded at www.pactrans.org | | | |
| 16. Abstract <p>Bridge inspection is a critical task needed to monitor bridge quality and serviceability. In the U.S., 40 percent of bridges are more than 50 years old, while most bridges are typically designed for a lifespan of 50 years. Of the 614,387 bridges across the U.S., 9.1 percent are considered structurally deficient. These statistics reported in the literature emphasize the urgent need for more frequent and comprehensive bridge inspections. However, the current manual inspection routine is expensive, time-consuming, hazardous, and subjective. Moreover, current Bridge Management Systems (BMS) may not coordinate management of all four phases of the bridge life cycle. Also, dispersion of inspection data drastically reduces the effectiveness of these systems. Therefore, there is a need to find cost-efficient and productive ways to inspect and manage our bridges.</p> <p>The objective of this study was to develop a novel framework for performing bridge inspections and management. The framework implements Bridge Information Modeling (BrIM) and unmanned aerial system (UAS) technologies to solve the problems with current manual bridge inspection and management practices. The proposed framework was implemented with data collected from an existing bridge located in Eugene, Oregon. Different types of defects were identified from the digital images captured by the UAS, and cracks were detected automatically by applying computer vision algorithms to those images. The identified defects were assigned to individual BrIM elements. BrIM was used as the central database to store the 3D bridge model and all inspection data. The framework also enables bridge inspectors and decision makers to access the most up-to-date inspection data simultaneously by taking advantage of cloud computing technology. The proposed framework will (1) provide a systematic approach for collecting and accurately documenting structural condition assessment data, (2) reduce the number of site visits and eliminates potential errors resulting from data transcription, and (3) enable a more efficient, more cost-effective, and safer bridge inspection process.</p> | | | |
| 17. Key Words Bridge Information Model; Unmanned Aerial Systems; Bridge Inspection | | 18. Distribution Statement No restrictions. | |
| 19. Security Classification (of this report) Unclassified. | 20. Security Classification (of this page) Unclassified. | 21. No. of Pages 57 | 22. Price NA |

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List of Abbreviations (optional)

AEC-FM: Architectural / engineering/ construction and facilities management
ASCE: American Society of Civil Engineers
BIM: Building Information Modeling
BME: Bridge management elements
BMS: Bridge Management System
BrIM: Bridge Information Modeling
CS: Condition state
FHWA: Federal Highway Administration
GPR: Ground-penetrating radar
IFC: Industry foundation classes
IPD: Integrated project delivery
IR: Infrared
TLS: Terrestrial laser scanners
MBE: Manual for Bridge Evaluation
NBEs: National bridge elements
ODOT: Oregon Department of Transportation
PacTrans: Pacific Northwest Transportation Consortium
TLS: Terrestrial laser scanner
WNN: Wavelet neural network
WSDOT: Washington State Department of Transportation
UAS: Unmanned aerial system

Acknowledgments

The authors would like to thank the Pacific Northwest Transportation Consortium (PacTrans) for funding this research. The authors would also like to thank Nisha Puri for her help with data collection and the Oregon Department of Transportation (ODOT) for providing us with the drawings and inspection data for the bridge used in the case study.

Executive Summary

The mobility of a nation's people and goods is highly dependent on the health of its transportation system. However, the U.S. infrastructure has been repeatedly graded in poor condition (ASCE, 2017; Petroski 2016), and the budget available to either repair or replace these structures is limited (USDOT, 2017). Timely inspection and effective maintenance of bridges are crucial to avoid any issues that may have a negative impact on public mobility. However, current bridge inspection practices inhibit the collection and analysis of information about the status of bridges in an efficient and timely manner. This problem is further exacerbated by the large number of bridges in the U.S., and the limited number of inspectors available. For example, in Oregon, because there are more than 6,000 bridges and Oregon Department of Transportation (ODOT) employs only about 25 inspectors, a substantial number of subcontractors must be hired to carry out the work.

Current bridge inspection practice requires experienced inspectors to record relevant data manually using checklists and paper notes, which is subjective and inefficient. In addition, inspectors are exposed to a variety of safety risks in the field, especially when using lifting equipment. Such equipment is expensive and interrupts traffic. Furthermore, current bridge management systems are considered to be inefficient, as they group similar types of elements together to report defects and fail to enable visualization of inspection data, which may hinder understanding of the underlying reasons for deficiencies of an individual component, especially with the increasing amount of information obtained from each bridge inspection. Furthermore, such inspections do not provide interoperable solutions throughout the entire bridge life cycle.

This study developed a novel bridge inspection framework for mitigating the problems that have been identified in current bridge inspection and management practices. The framework

implements camera-based unmanned aerial systems (UASs), along with computer vision algorithms, to collect and process inspection data, and Bridge Information Modeling (BrIM) to store and manage all related inspection information. To test the framework's feasibility and efficiency, an illustrative case study was conducted on an existing bridge in Eugene, Oregon, using the proposed framework.

The proposed framework provides bridge data in the form of digital images and 3D models in a central database that is simultaneously accessible to all stakeholders via cloud computing. The case study results verified the following:

- (1) High-resolution images collected with a UAV enabled visual identification of different types of defects and automatic detection of cracks using computer vision algorithms.
- (2) The use of BrIM enabled defect information to be assigned to individual model elements and all bridge data to be managed in a single model across the bridge life cycle.

The proposed framework is expected to help transportation agencies \ (1) collect and document accurate bridge inspection data; (2) reduce the time and number of site visits and eliminate potential errors resulting from data transcription; and (3) conduct a more efficient, cost-effective, and safer bridge inspection process.

Chapter 1 Introduction

The strength and growth of the U.S. economy, as well as the quality of life of all Americans, highly depend on the condition of its infrastructure, such as its road network and bridges. However, previous studies have indicated that the U.S. infrastructure is aging and that its road network and bridges are being poorly maintained for decades. In August 2007, the I-35W Mississippi River Bridge suddenly collapsed during evening rush hour, resulting in 13 fatalities and 145 injuries. This bridge was rated as “structurally deficient” by the federal government in 1990 because of significant corrosion in its bearings (Mahmoodian *et al.*, 2007). Similarly, in May 2013, the I-5 Skagit Bridge near Seattle, Washington, collapsed into the river below after being struck by an oversized truck. Three people were seriously injured, and the incident affected an average of 71,000 drivers who relied on this bridge to commute daily. Most recently, in March 2018, a pedestrian bridge that connects Florida International University with a neighboring city collapsed. Engineers claimed that the collapse was due to a key mistake in the design and placement of one of its support towers, and cracks appearing on the bridge did not get enough attention, resulting in the deaths of six and injuries to more than a dozen people (Laris and Syrluga, 2018). These catastrophes have raised the public’s attention to the condition of the nation’s bridges and their maintenance operations.

1.1 Current Bridge Conditions in the U.S.

The most recent Infrastructure Report Card released by the American Society of Civil Engineers (ASCE) gave the nation’s infrastructure an overall grade of D+ (poor) and its bridges a grade of C+ (mediocre). Of the 614,387 bridges in the National Bridge Inventory, 15 percent are 40 to 49 years old, and 40 percent are over their 50-year designed life span (figure 1.1). An average bridge age of 43 years old indicates that an increasing number of bridges are facing the

need for major maintenance or rehabilitation. In addition, 9.1 percent of bridges were classified as structurally deficient in 2016 (ASCE, 2017). Structurally deficient bridges are not necessarily unsafe or likely to collapse. However, their critical load-carrying elements are in poor condition as a result of deterioration or damage, so they need more frequent monitoring to eliminate possible and potential collapse. Although the federal government has increased investments to fix bridges in recent years and the number of structurally deficient bridges is decreasing, the budget available for bridge rehabilitation and repair is limited, and the backlogged budget has reached \$123 billion (ASCE, 2017). In summary, because of the U.S.'s aging and deteriorating road and bridge systems and limited budget, there is an urgent need for an efficient and cost-effective bridge inspection and management process that can reduce or even prevent structural failures.

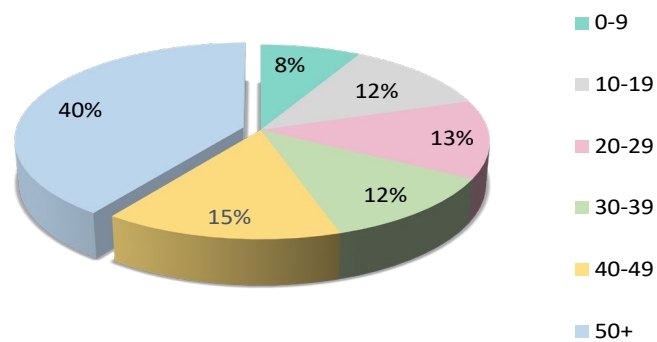


Figure 1.1 America's bridges by age (Source: ASCE, 2017)

1.2 Objectives

The main goal of this study was to provide an accurate, effective, and cost-efficient solution for bridge inspection and management. To achieve this goal, a systematic bridge inspection framework was developed to satisfy the demands related to inspection frequency, safety,

efficiency, and cost-effectiveness. Three specific objectives were identified as integral pieces of this study.

First, to better understand current bridge inspection and data management practices and to identify existing problems associated with both inspection and data management stages, the Federal Highway Administration's (FHWA) National Bridge Inspection Standards and Oregon Department of Transportation's (ODOT) Bridge Inspection Program Manual were examined. In addition, inspection reports and literature from other related studies were used to identify all issues encountered in current bridge inspection and management processes. This process helped us to define the problem and gain a better understanding of related issues in a national context.

Second, the most recent studies on the implementation of a variety of technologies for bridge inspections, and management were evaluated to better understand the advantages and disadvantages associated with each technology. This helped us to identify the research gap and needs. Ultimately, the goal of this project was determined to be development of a more effective framework for bridge inspections and management that has practical implications.

Lastly, this study sought to develop a novel framework using the most suitable technologies to improve current bridge inspection and management practices in terms of safety, efficiency, duration, and cost. Furthermore, the feasibility and applicability of the proposed framework were evaluated by testing the framework on an existing bridge \ and comparing the results with those obtained by using traditional methods. The implementation of the proposed framework is expected to 1) provide a systematic approach for collecting and accurately documenting structural condition assessment data; 2) reduce the number of site visits and eliminate potential errors resulting from data transcription; and 3) enable a more efficient, more cost-effective, and safer bridge inspection process.

1.3 Organization of the Report

This report is organized as follows: Chapter 2 provides a comprehensive literature review on current bridge inspection practices and several advanced technologies that are used for bridge inspections. Chapter 3 presents the research methodology by detailing the proposed bridge inspection and management framework. Chapter 4 describes the study site and details the data collection procedure. Chapter 5 presents the results of the case study described in Chapter 4 and evaluates the efficiency of the proposed framework. Chapter 6 provides a discussion on the case study results, as well as the limitations of the proposed framework. Chapter 7 draws conclusions and discusses future research needs. The organization of the report is schematically outlined in figure 1.2.

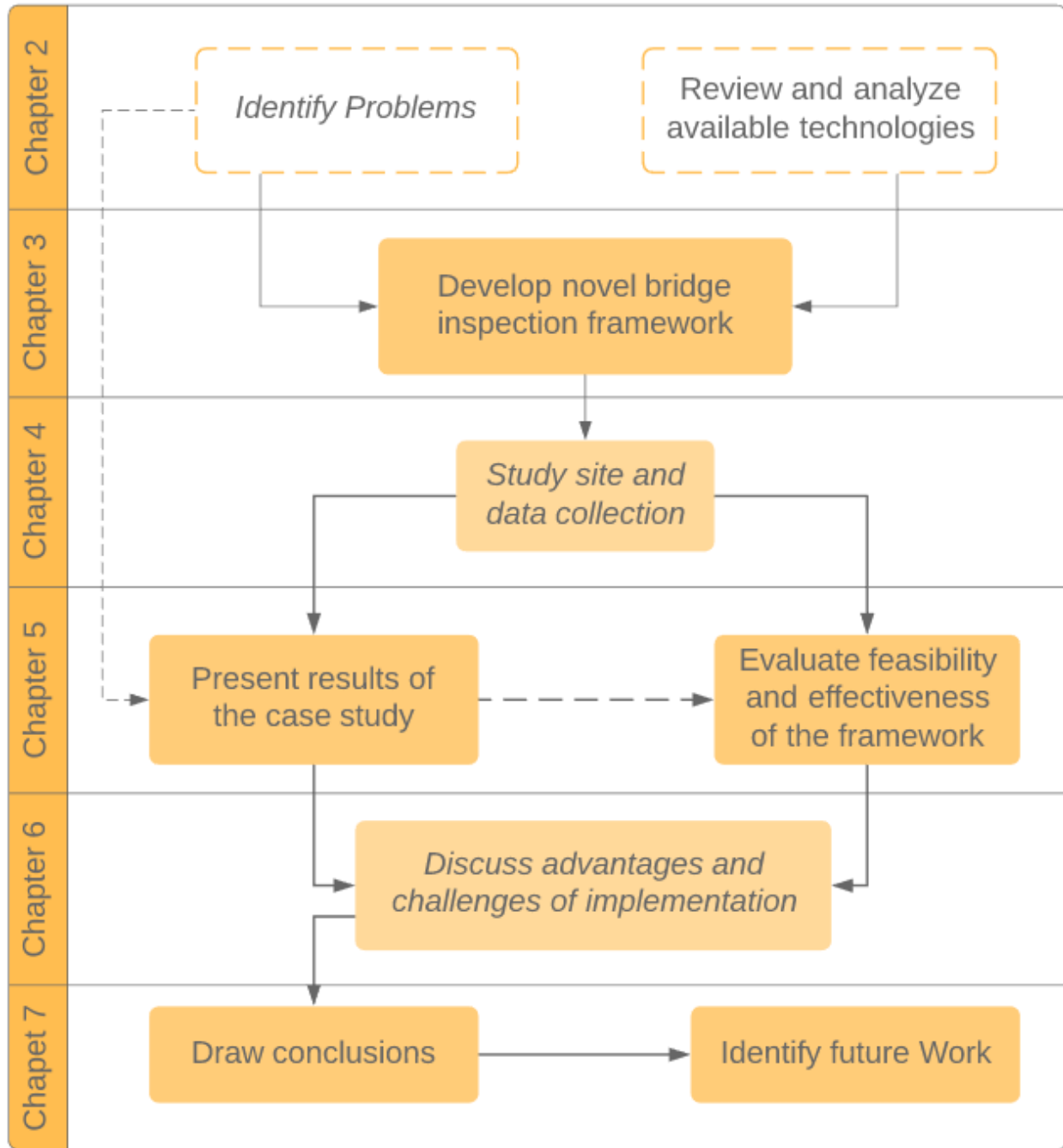


Figure 1.2 Flow chart of report organization

Chapter 2 Literature Review

Bridge inspections are critical for monitoring bridge quality and serviceability, as they provide detailed information regarding bridges' structural stability. However, current visual and paper-based bridge inspection practices are considered time consuming, inefficient, and expensive. Several studies demonstrated that the use of advanced technologies such as unmanned aerial systems (UAS), laser scanners, and Bridge Information Models (BrIM) can help improve current bridge inspection practice. This section provides a comprehensive review of the literature on studies of advanced technologies for data collection, processing, and management to improve current bridge inspection and management practices. In addition, the advantages and disadvantages of using these technologies are analyzed, and the gaps between using these technologies and current practice are identified.

2.1 Current Bridge Inspection and Management Practices

The AASHTO Manual for Bridge Evaluation (MBE) identifies seven types of inspections: initial, routine, damage, in-depth, fracture critical, underwater, and special (AASHTO 2011). The inspection frequency and detail level vary depending on the types of inspections, as well as bridge conditions. The most common type of inspection, the periodic routine inspection, is typically based on visual observation and/or basic measurements to identify any bridge defects or changes from previous records. For deficiencies that are not readily detectable using routine inspection procedures, unscheduled and more hands-on inspections, such in-depth inspections, may be necessary.

The Federal Highway Administration (FHWA) requires that all states perform biennial routine inspections of each bridge (AASHTO 2011) and recommends at least annual inspections of bridges rated as structurally deficient (ASCE 2017). The procedures involved in a routine

inspection differ significantly depending on the type of bridge, mainly because different defects tend to be related to different materials. Concrete cracks, for example, are the primary focus of routine inspections of concrete bridges.

Current basic routine bridge inspections typically use visual and paper-based practices. First, a qualified inspector correctly identifies the type, location, and severity of defects on each bridge element within arm's reach following a planned sequence (using an element numbering system). Second, the inspector manually records the damage by using checklists, taking notes, drawing sketches, and taking photos while on site. Finally, the inspector evaluates all elements and documents all data using standard inspection reports, which s/he uploads to the Bridge Management System (BMS) after returning to his/her office. The BMS enables bridge engineers to access and compare their reports with previous inspection results and identify any repair/rehabilitation/maintenance needs.

Documentation is essential for bridge inspection. The FHWA requires that every bridge inspection be accompanied by an inspection report (Ryan et al. 2012). The standard inspection report includes evaluations of both national bridge elements (NBEs) and bridge management elements (BMEs), which are presented in element condition states (CS) (table 2.1). NBEs are bridges' primary structural elements, such as their superstructures or reinforcement closed box girders, while BMEs are elements such as joints and protective systems. Both are necessary to determine the overall condition and safety of a bridge's primary load-carrying members. In addition, all defects are grouped and quantified. The severity of each grouped defect is reflected by four levels of condition states: good, fair, poor, and severe. On the basis of the element condition and a detailed deficiency description, a condition rating, appraisal rating, and load rating are calculated to determine the bridge's serviceability and maintenance needs.

Table 2.1 Sample element condition states

| Element | Defects | Quantity | Units | Env. | CS 1 | CS 2 | CS 3 | CS 4 |
|---------------------------------|--------------------------------------|----------|-------|------|------|------|------|------|
| 105-Re Clsd Box Girder | | 6000 | (LF) | Mod. | 0 | 2500 | 3500 | 0 |
| | 1120-Efflorescence/ Rust Staining | 1500 | LF | Mod. | 0 | 1500 | 0 | 0 |
| | 1130-Cracking | 4500 | LF | Mod. | 0 | 1000 | 3500 | 0 |
| 302-Compressn Joint Seal | 2310=Leakage | 100 | LF | Mod. | 0 | 0 | 0 | 100 |

2.2 Problems Identified in Current Bridge Inspection and Management Practices

Several shortcomings are associated with current visual and paper-based inspection and data management practices. First, inspectors may be exposed to safety risks while performing the inspection and evaluation, especially when attempting to reach areas with limited accessibility (e.g., the bottom of overwater bridges). Second, equipment used for inspections, such as elevating platforms and scaffolding, are expensive and may affect traffic severely as it may require lane closures (Hallermann and Morgenthal 2014). Third, because the evaluation of all elements is based primarily on the inspector’s judgment, the evaluation process is not objective and may be impacted by the inspector’s experience, which may affect the accuracy of the inspection results (Bu et al 2014). Fourth, the element-based bridge inspection procedure typically takes several days, depending on the size of the bridge. Average bridge inspection costs per bridge range between \$4,500 and \$10,000 (Zulfiqar *et al.*, 2014). The process is time-consuming, laborious, and costly, especially for large and complex bridges.

Moreover, given the increasing amount of information generated from different types of bridge inspections, current BMSs can be inefficient for several reasons. First, current BMSs do not satisfy the growing need to coordinate management of all phases of an entire bridge life cycle (Shirolé et al. 2009; Shirolé 2010; Sacks *et al.*, 2018). Many current BMSs contain mainly bridge

inventory data and inspection data, which do not provide the information needed for subsequent bridge repair/rehabilitation/maintenance work. Other data, such as design data and as-built data, are needed to support better decision making (Sacks et al. 2017). Second, current BMSs typically focus on databases but not provide direct representation or visualization of the data (Chan et al. 2016). Third, current database-oriented BMSs group similar types of elements together to report defects and provide no direct representation or visualization of inspection data, which may hinder understanding of the underlying reasons for deficiencies of an individual component (Chan *et al.*, 2016). This becomes worse when different project teams input a large amount of inspection data to current BMSs, as key information can be obscured by the low efficiency of these systems. This can often prevent engineers from fully understanding how the condition of a structure has changed over time (DiBernardo, 2012; Chan *et al.*, 2016)

This discussion illustrates that there is an urgent need to develop a new bridge inspection and management approach that is effective, efficient, and inexpensive. To address the weaknesses inherent in current visual bridge inspection processes, previous studies have proposed several ideas to implement various new technologies to improve inspection and management practices. These are discussed below.

2.3 Technologies Used for Inspection Data Acquisition and Processing

Previous studies have proposed methods to improve current bridge inspection processes by implementing advanced remote sensing data collection and processing technologies. Remote sensing technologies enable data collection with equipment that has no physical contact with the target. Remote sensing technologies can be categorized into two groups based on their data collection range and purpose, which are determined by the electromagnetic signal, and can detect both subsurface and surface defects.

2.3.1 Remote Sensing-Based Approaches for Subsurface Defect Detection

Subsurface defects, such as reinforcement corrosion and concrete delamination, are not visible but can directly reduce elements' structural capacity and be harmful to the entire structure. Detecting subsurface defects and measuring their severity are critical tasks for in-depth bridge inspections. Ground-penetrating radar (GPR) is a technology that uses high-frequency electromagnetic waves to acquire subsurface information by penetrating a surface and detecting signals reflected by different buried objects and layers of materials. GPR has been used for concrete and masonry bridge inspections, especially for deck condition assessments, and has shown promise for better detecting the size and location of concrete delamination areas on bridge decks than visual inspection methods (Shamsudin et al. 2015). However, the principle issue with GPR technology is the slow rate of data capture when the evaluation depth is more than 3 inches (Ryan et al. 2012). There are two main procedures for analyzing GPR data: a visual method and a numerical method. The numerical method typically uses amplitude variations to analyze the internal conditions of specific elements. The visual method, on the other hand, is typically based on an expert's assessment of the GPR profiles. Tarussov et al. (2013) evaluated these two methods and concluded that the visual method is more accurate than the numerical method, mainly because the quantitative method overlooks some important information in the GPR profile, such as changes in reinforcing bar spacing and changes in slab thickness. However, the visual method also suffers the shortcoming of subjectivity, since the results are highly dependent on the experience and judgment of the analyst.

Infrared (IR) thermography is another remote sensing technology used for detecting subsurface defects in bridge inspections and evaluations (Dabous et al., 2017). The basic theory behind IR thermography is that the amount of heat conducted through a material will change in

the presence of a subsurface defect. Hence, the defects can be identified by using the IR imaging of the element based on the change of its surface temperature. Because this technology involves collecting and analyzing objects' radiation and IR energy, temperature differences between daytime and nighttime should be considered when the technology is used (Washer et al., 2010). During the daytime, sunlight increases the temperature of the bridge surface, while undersurface defects maintain a lower temperature. This phenomenon can lead to different results when IR thermography is used during the daytime and nighttime. Although IR thermography is easy to use and not expensive, its main disadvantage is the accuracy of detection, which can be easily affected by different environment conditions (e.g., temperature, sunlight) (Vaghefi et al., 2011).

Because of the limitations of the various technologies described above, Dabous et al. (2017) suggested integrating GPR and IR thermography to enhance the accuracy and reliability of data collection and processing for subsurface delamination detection. Although this approach is comprehensive and more objective than traditional bridge inspection practices, its main challenges are its limited environment implementation and the need for sufficient technological knowledge to interpret the data.

2.3.2 Remote Sensing-Based Approaches for Surface Defect Detection

Surface defects such as cracks, spalling, and efflorescence are indicators of possible subsurface defects and need to be monitored regularly. Terrestrial laser scanners (TLS), which are known for their ability to rapidly obtain accurate information from structures' surface and present this information in the form of three-dimensional (3D), high-density point clouds, have also been used for bridge inspections. Truong-Hong et al. (2016) developed a framework that utilized TLS technology to inspect bridges for deformation and damage. Their study showed that the information provided by TLS is sufficient for bridge condition assessment. However,

although TLS can provide high-resolution and accurate output, the resulting large file sizes and long data processing times are considered to be two primary barriers to its wider adoption in the architectural, engineering and construction, and facilities management (AEC-FM) industry (Turkan *et al.*, 2016, Valenca *et al.*, 2017). Turkan *et al.* (2016) developed a novel adaptive wavelet neural network (WNN)-based approach to overcome some of the drawbacks associated with using TLS technology for bridge inspections. Their approach detected concrete cracks by using an adaptive WNN in low-resolution TLS point clouds, enabling the rapid processing of 3D point cloud data and the automatic detection of cracks. However, from an economic perspective, TLS is still not considered to be an optimal option. Ravanel and Curtaz (2011) compared TLS and photogrammetry technologies and concluded that the cost of TLS without annual maintenance fees tended to be approximately six times or more expensive than using photogrammetry.

Another remote sensing technology that is used to detect surface deteriorations is the unmanned aerial system (UAS). Because of the advantages of UASs in terms of safety, cost performance, and operability (Liu *et al.*, 2014), it has been well received and tested for a variety of applications in the construction industry. With advancements in camera technology, high-resolution images and videos captured by UASs have been shown to improve jobsite safety by providing better visualization of working conditions (de Melo *et al.*, 2017). Images collected by UASs regularly, e.g., every week or every other week, enable monitoring changes on a construction site and documenting construction progress (Lin *et al.*, 2015). UAS technology has received significant attention in the infrastructure inspection field as well. Its remote-control features and ability to fly very close to a structure have led to its frequent use on-site to separate inspectors from potential workplace hazards (Karakhan *et al.*, 2019). In addition, UASs are

considered to have little impact on traffic flow, and they eliminate the costs from utilization of expensive lifting platforms used in traditional bridge inspection (Metni *et al.*, 2007). Moreover, the high-quality images captured by UASs provide results comparable to those from traditional bridge inspections (Otero 2015), especially when identifying concrete spalling, cracks, and potential defects in bridge connections (Gillins *et al.*, 2018; Lee *et al.*, 2018). With the help of computer vision techniques, Khaloo *et al.* (2018) reconstructed a 3D model of a bridge in Alaska based on images captured by a UAS. This 3D model proved to be very helpful for organizing images and locating bridge defects. Another study tested the feasibility of using UASs to detect cracks under controlled conditions, both in real-time and during post-processing (Dorafshan *et al.*, 2017). Although it is generally accepted that UASs are assistive and useful tools for structural inspections, the image quality is sensitive to environmental factors such as lighting conditions and winds (Hallermann and Morgenthal, 2014; Morgenthal and Hallermann, 2014).

2.4 Technologies Used for Inspection Data Acquisition and Processing

Building Information Modeling (BIM) has revolutionized the AEC-FM industry. BIM is widely accepted both as a technology and a process. From the technology perspective, BIM is software that virtually simulates building components by generating a single virtual 3D model, which enables all building information and construction documents to be linked to the model components (Eastman *et al.*, 2011; Azhar, 2011; Azhar *et al.*, 2015). BIM models are principally different from 3D CAD because they are built on object-oriented databases that enable simultaneous and automatic updates of changes in building elements across all views (Azhar *et al.*, 2015). From a process perspective, BIM has changed the way projects are built by encouraging and creating a more collaborative environment for project teams. The majority of the projects that implement BIM are delivered with integrated project delivery (IPD) or design-

build methods, which enable early involvement of all project stakeholders (Eastman et al., 2011). BIM also enhances team communication and collaboration by transferring and sharing the BIM model among different project parties. This is done through the use of industry foundation classes (IFC), a neutral file format that improves the interoperability among different applications through the entire project life (Eastman et al., 2011).

Bridge Information Modeling (BrIM) is a term for BIM when it is used specifically for bridge projects. Although some pilot projects have implemented BrIM during the design and construction phases, BrIM implementation in existing bridges has been rare mainly because of the challenges associated with converting existing 2D, as-built drawings to 3D models (Volk et al., 2014). For the majority of the bridges in the United States, the only available as-built documentation is still in the form of 2D drawings. Therefore, appropriate modeling software is needed to convert 2D, as-built bridge drawings to 3D models. Several commercial software products are available, including Tekla Structures and Autodesk Revit, that are capable of creating accurate, reliable, and detailed 3D information models (McGuire et al., 2016). These platforms are widely used in the industry, as they enable the creation of custom families as well as the setting of user-defined parameters. Moreover, their ability to export interoperable IFC files, their most beneficial characteristic, enhances their compatibility among non-native file types. BrIM has also been considered for implementation in the operations and maintenance phases because of its abilities to provide better visualization of and interoperability among the structure's conditions for each component (Azhar et al., 2015; Marzouk and Hisham, 2012). DiBernardo (2012) proposed a framework that integrated inspection data with 3D BrIM. Following that work, Al-Shalabi et al. (2015) proposed a 3D BrIM-based inspection framework that implemented BrIM, mobile devices, and cloud computing. In that framework, mobile

devices were used in the field to access and add inspection data (e.g., crack types, sizes, etc.) to the bridge elements in the 3D BrIM model with the help of data cloud. This framework was tested by Iowa Department of Transportation (DOT) inspectors, who confirmed the potential benefits of implementing BrIM for bridge inspections. McGuire et al. (2016) investigated the use of BrIM for bridge inspection and evaluation by placing “damage cubes” on the model elements to visually represent defect severity. Although it is often noted that BrIM can be used over a project’s entire life cycle, only a few studies have implemented BrIM for bridge data management (Liu and Issa, 2015). In addition, a gap exists between on-site inspection data collection for existing bridges and integration of inspection data with BrIM models for bridge management.

Although previous studies have demonstrated various technologies that can be used to improve data collection, processing, and management, no systematic, end-to-end approach has been presented. Therefore, this study proposes a novel, systematic bridge inspection framework, built on Al-Shalabi et al.’s study (2015) that combines UAS and BrIM technologies. UASs enable safer and more rapid collection of bridge images and videos, which can be used for automatically detecting cracks or other defects with the help of computer vision algorithms. The defect information, such as type and severity, can be then assigned to individual elements in the 3D BrIM model, which enhances the visualization of the inspection data and eliminates data dispersion. All bridge information—including 2D drawings from different phases, integrated 3D information models, and all bridge inspection information—is stored in a central, object-oriented database, i.e., the BrIM, which can be accessed both from the office and in the field.

Chapter 3 Methodology

The main objective of this study was to develop a novel, systematic approach that implemented UAS and BrIM technologies to improve the efficiency of current bridge inspection and management practices. Figure 3.1 provides an overview of the proposed framework, which has three main phases: 1) development of 3D bridge as-built models; 2) UAS data collection and application of computer vision algorithms to the UAS images to detect any defects; 3) integration of image processing results into the 3D model, and uploading of the integrated information models to the data cloud for future inspections and data management.

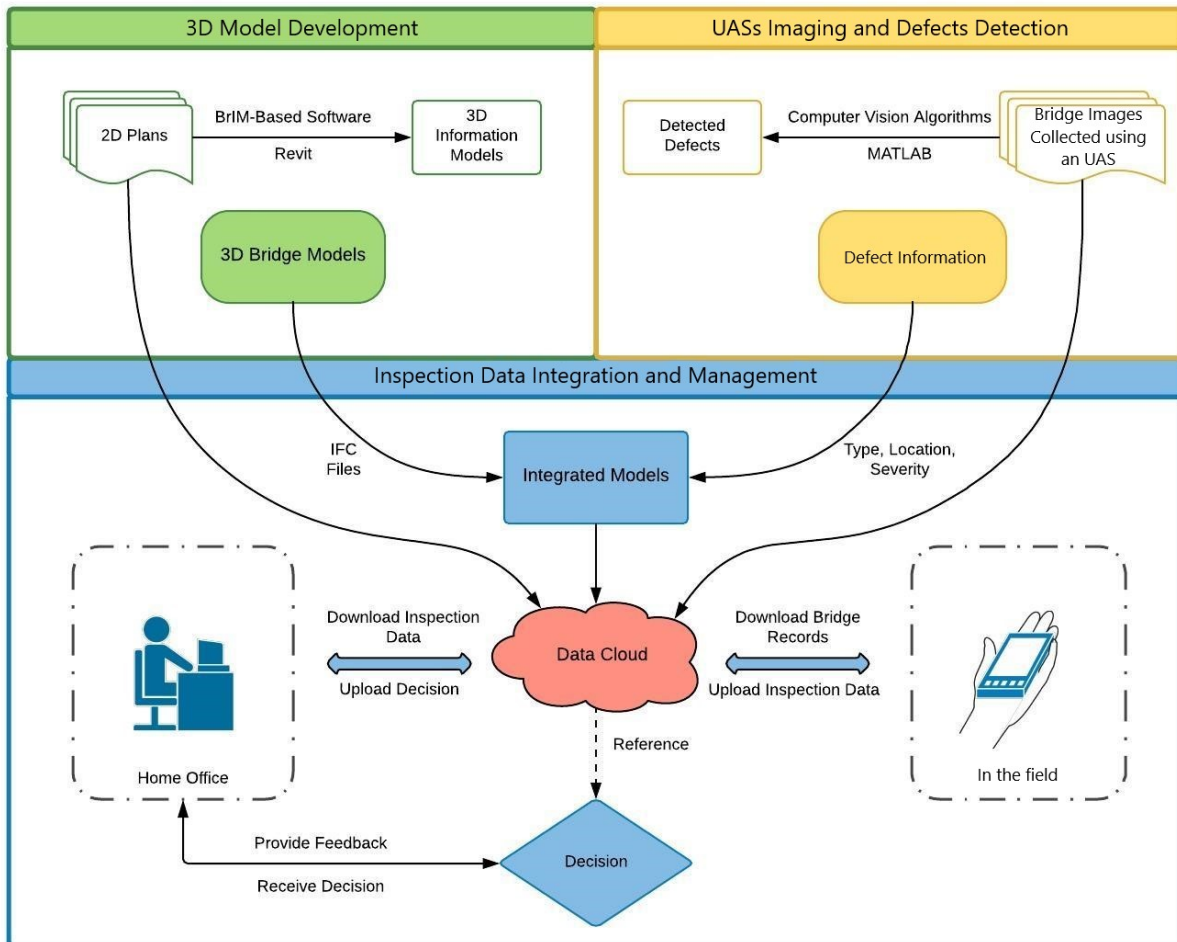


Figure 3.1 Proposed Bridge inspection and management framework

3.1 Bridge Model Development

In this study, Revit was used because of its availability to the research team. Revit is widely used in the industry, as it enables the creation of custom families, as well as the setting of user-defined parameters. Moreover, its ability to export interoperable IFC files, its most beneficial characteristic, enhances compatibility among non-native file types and provides the possibility for subsequent steps in the proposed methodology. To help bridge inspectors to adopt and use the proposed framework easily, the 3D models were developed at the element level by mimicking the traditional inspection method that is based on 2D, as-built plans. The bridge model elements were divided into major group types, such as deck, superstructure, and substructure, which follows the sequence of traditional bridge inspection. Elements that were not found in Revit's predefined library were created by customizing specific element families. In the Revit model, identification (ID) number and material type were provided for each element, which was the key to indexing each element, as well as to modifying information of a specific element in the IFC file. Revit software also enabled each group to be saved as a single model, which could be easily merged back together as a whole later. This functionality reduced the file size and made data transfer to and from the data cloud faster and easier.

3.2 Bridge Model Development

This phase was divided into three stages, which are schematically shown in figure 3.2.

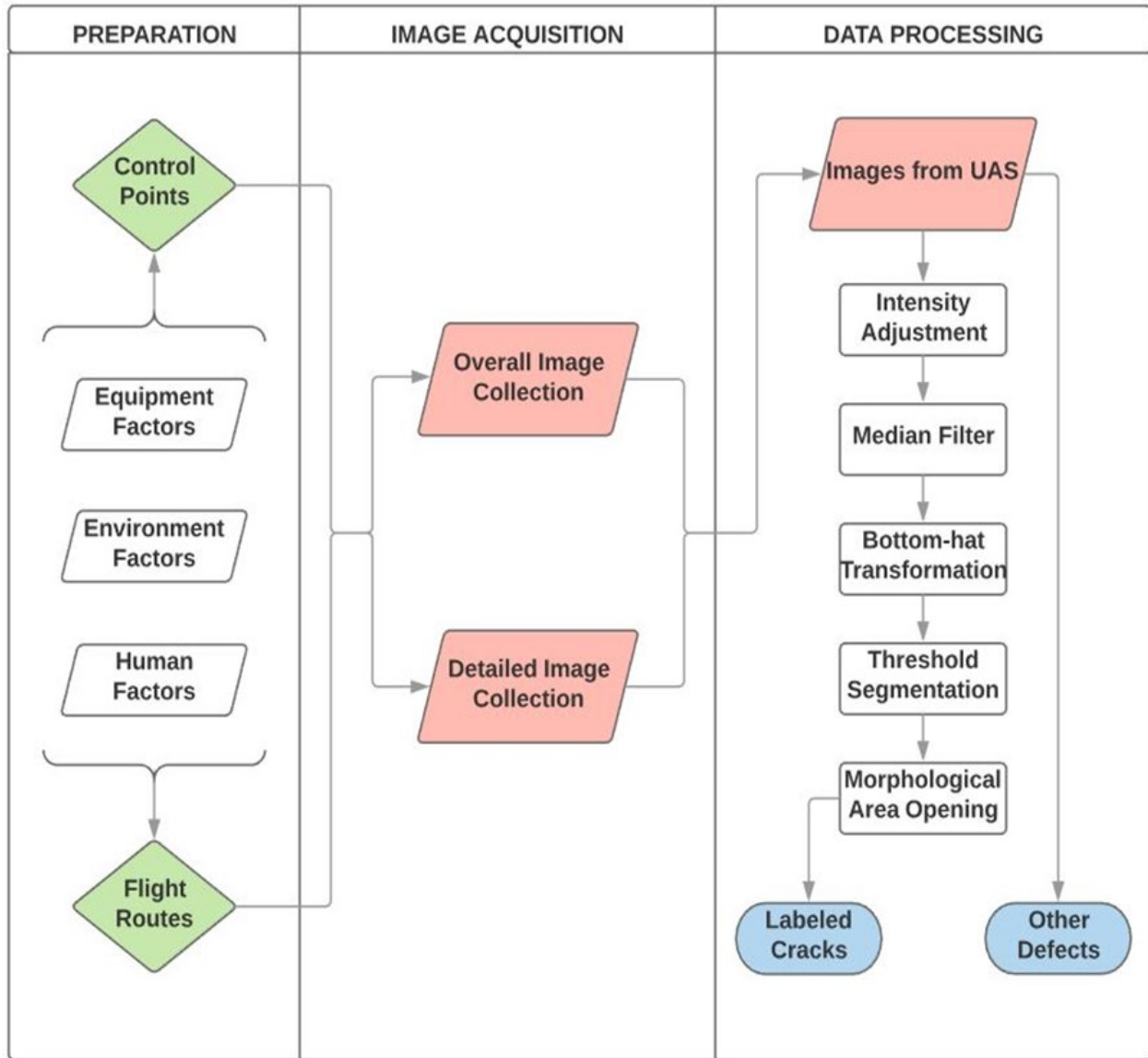


Figure 3.2 Overview of UAS imaging and processing phase

3.2.1 Flight Planning

To collect useful images using UASs in a safe and effective manner, it is necessary to first formulate a comprehensive imaging plan, which basically includes the design of control location(s) and the plan for flight route(s). Control locations are takeoff points, as well as the place where the pilot stands, while flight routes are the lines that UASs need to follow. Several

factors must be considered when imaging plans are designed: (1) equipment-based factors, (2) environment-based factors, and (3) human-based factors.

Equipment-based factors, such as aircraft size, battery capacity, and control range, typically determine how far and how long an aircraft can fly within a safe and visible range for the pilot. Familiarity with these factors is fundamental for designing the optimal number of control locations and flight routes based on the shape and size of the target bridge.

Environment-based factors typically reflect weather conditions and obstacles around the target bridge. In particular, weather factors such as wind can have a huge impact on the stability of the aircraft and the pilot's level of comfort controlling the UAS, especially for small and low-weight UASs. Moreover, obstacles such as trees affect the operator's view and may affect the safety of the aircraft. In these situations, it may be necessary to add additional flight-route segments and control points.

Human-based factors have to do with the pilot's skill and his/her level of comfort operating the aircraft. These factors dramatically affect the quality and resolution of the images. Although most UASs provide a first-person perspective on the controller, given the variability of human-based factors, it is highly recommended that a second viewer observe the flight paths to ensure safe operation of the aircraft.

3.2.2 Image Acquisition

After choosing appropriate control points and flight routes, images are acquired through a two-step approach to obtain images containing all the defects on the target bridge with a sufficient level of detail: overall image collection and detailed image collection. Overall image collection is important for providing an overall picture of the entire bridge and identifying regions of interest, i.e., concrete defects or cracks, for the next step. Intervals along the planned flight path are

manually set to collect images with sufficient image overlap. This step is helpful for identifying the orientation of the bridge and providing background for later indexing the detailed images. In addition, the real-time view displayed on the controller can help identify areas from which to collect detailed images. Detailed image collection is performed to gather more details about defects of interest that are identified during overall image collection. The images from the overall collection are captured farther from the bridge than detailed images, making it difficult to see details. Defects such as fine cracks are often visible only from close proximity, which satisfies the inspection requirement of arm's-reach distance.

3.2.3 Data Processing

The images collected by the UAS are processed to detect cracks automatically, which reduces the time required to manually examine each image. Before this step, the original images collected by the UAS are converted to grayscale images. The following steps are then performed with MATLAB image processing tools: (1) adjust the intensity values to increase the image contrast; (2) apply a median filter to each image to reduce noise; (3) utilize bottom-hat morphological operations to extract dark regions from the background; (4) apply threshold segmentation to separate cracks from those regions extracted in the previous step, producing binary images; and (5) perform morphological area opening to reduce the number of connected regions under a certain size and label cracks by using bounding boxes based on region properties. These steps are detailed below, and further information can be found in work by Xu and Turkan (2019).

Intensity adjustment is used to increase the contrast of the grayscale image. This operation maps the pixel intensity values in the grayscale image to a new values range, which is stretched by specifying new lower and upper limits. By default, the intensity adjustment in the MATLAB

image processing toolbox saturates the bottom 1 percent and the top 1 percent of all pixel values. Median filters are nonlinear operations often used in image processing to reduce “salt and pepper” noise and preserve edges. The median filter is an applied window matrix (m-by-n) that slides through each pixel x and replaces the pixel by using the median value of the surrounding m-by-n neighborhood. MATLAB performs median filtering of the matrix by using a default three-by-three neighborhood. Bottom-hat transformations are used to extract dark regions from the de-noised gray-level image f . Because the gray levels of cracks are usually lower than those of other regions, a bottom-hat transformation is applied to extract the structure with lower gray-level pixels from a bright background. Mathematically, this transformation of image f_{BHT} can be expressed as follows (Bai *et al.*, 2012):

$$f_{BHT} = f_{Bn} - f \quad (3.1)$$

where f_{Bn} is the new closing image set of structuring element Bn , which is dilated n times using a morphological dilation operator. The structuring element Bn can be a round, linear, or square shape, depending on the shape of the object (the shape of the defect in this case) that is being processed.

Threshold segmentation is used to separate the cracks from the image set (f_{BHT}) obtained in the previous step. Following the bottom-hat transformation, dark regions are detected as objects (defect/crack) and bright pixels are set as the background. However, not all dark regions are cracks, and some dark regions that are not cracks are also extracted as objects in the obtained image set. It is important to separate cracks from regions with certain gray levels. Otsu (1979) proposed a method to find the optimal threshold T to separate pixels into two classes, which can be expressed as follows:

$$\omega_B \omega_O (\mu_O - \mu_B)^2 |_T = \text{Max}_{0 \leq k \leq 255} \omega_B \omega_O (\mu_O - \mu_B)^2 \quad (3.2)$$

where ω_B and ω_O denote the background occurrence probability and the objective occurrence probability, respectively, and μ_B and μ_O denote the background mean levels and objective mean levels, respectively. Thus, the pixels in the previous image set can be separated into two classes using T . If the gray level of the pixels in f_{BHT} is higher than T , the pixels will be attributed to white (replaced with one), and if the gray level is lower than T , the pixels will be attributed to black (replaced with zero). This step produces a binary image.

A morphological area opening is used to remove small objects from the binary image. Because some small regions or pixels are misidentified as cracks, this operator is used to remove connected components with pixels that are under a certain value. Pixel x in the filtered object can be expressed as follows (Vincent, 1994):

$$f_{AO}(x) = \begin{cases} f_T(x), & N_x \geq N_p \\ none, & N_x < N_p \end{cases} \quad (3.3)$$

where $f_T(x)$ is pixel x in the connected components after thresholding of the binary image, N_x denotes the number of pixels (i.e., the area) in those connected components, and N_p denotes the pixel number p . If the area of the component is larger than p , the object is kept; otherwise, it is removed. The p value can be set according to the specific situation. The area property of the filtered components is used to label the crack region using the smallest possible rectangle bounding box.

3.3 Inspection Data Integration and Management

The image processing results—information obtained about cracks and other defects (e.g. type, orientation, and location) on the bridge—can then be assigned to individual bridge elements by modifying the IFC file. Finally, the integrated 3D bridge models, along with historical inspection documents and the images captured by the UAS, are uploaded to the Autodesk data cloud, which can be accessed from both the office and the jobsite. The severity of

each element's defects can be reflected on the 3D-integrated models with four colors: green (good), yellow (fair), orange (poor), and red (severe), just as in a traditional bridge inspection report.

Chapter 4 Case Study

To demonstrate the feasibility and efficiency of the proposed framework, an illustrative case study was conducted on an existing bridge located in Eugene, Oregon. The primary objective of this experiment was to evaluate whether the proposed framework can help improve conventional bridge inspection practices by producing accurate results faster and in a more cost-effective way while enabling better management of bridge data. This section describes the data collection procedure and the results of the experiment in detail.


4.1 Study Site and Equipment

The bridge selected for this study was located on highway I-105, which spans over the Willamette River in Eugene within Lane County, Oregon. This 844-ft-long and 81.17-ft-wide concrete bridge was constructed in 1967, so it was past its 50-year design life. The bridge is inspected by the Oregon DOT's Bridge Inspection Program every two years. Mainly because of its poor deck condition, it was classified as structurally deficient in the last available inspection report. The aircraft used in this study was a DJI Mavic Pro, which was provided by the Oregon State University research office. The market price for the selected UAS was around \$1,000, which was relatively low in comparison to other UASs available on the market. Figure 4.1(a) presents an image of the study site captured by the UAS. Table 4.1 lists the specifications of the UAS used in this study, which reflect the theoretical parameters (factory settings) of the aircraft. The aircraft was controlled with a remote controller, which was connected to an Android phone (it would also work with an iPhone). The DJI Mavic Pro application was installed on the phone, which provided a real-time view for the pilot operating the UAS. The DJI Mavic Pro application enabled adjusting exposure levels when collecting images, which partially reduced the effects of illumination issues.



Figure 4.1 (a) The study site, Eugene, OR; (b) Plan for control points and flight routes

Table 4.1 Equipment specifications

| Classification | | Description |
|--------------------------------|--------------------------------------|--|
| Maker/Name | | DJI/Mavic Pro |
| Actual Image | |  |
| Aircraft Specifications | Folded Size | L198mm x W83mm x H83mm |
| | Weight | 1.62 lbs (Battery & Propellers Included) |
| | Overall Flight Time | 21 minutes per battery package (In normal flight, 15% remaining battery level) |
| | Satellite Positioning Systems | GPS/GLONASS |
| Camera Specifications | Resolution | 12.35 MP |
| | Maximum Image Size | 4000 x 3000 |
| | Gimbal Controllable Range | Pitch: -90° to +30° |
| | | Roll: 0° or 90° (Horizontally and Vertically) Yaw: -60° to +60° |

4.2 Data Collection

The UAS was operated on December 1 and 7, 2017, because of good weather conditions, without strong winds for the flight. Figure 4.1(b) presents the control points and the flight routes that were determined before the data collection. Both the control points and the flight routes were determined by taking the equipment-, environment-, and human-based factors into account, which were detailed in the framework development section. The battery capacity of the UAS was

21 minutes per flight. Nevertheless, each flight was set up to be 15 minutes to reserve sufficient time for a safe return. Because of the small size (1.62lbs) of the UAS and the rough and uneven plants and trees along the river bank near the bridge, as well as the pilot's skill level and the operational safety, two control points were set along the two sides of the bridge. Furthermore, because of the large aspect ratio of the bridge's structure, flight routes were set along the long sides to support optimal image coverage of the bridge.

Manual flight mode was used for both overall and detailed data collection in this study. The overall data collection was performed by flying the aircraft along the flight routes with three different view angles: 30° above the deck, perpendicular to the deck, and 30° below the deck (the gimbaled camera could pitch up to 30°). The distance interval of hovers was manually controlled, and the UAS was kept to approximately 15 ft to 20 ft away from the bridge during overall imaging. The horizontal distance interval of adjacent hovers was manually controlled at around 70 ft based on the basis of the yaw range of the camera. The pilot yawed the camera at each hover position to capture high-resolution images with sufficient overlap, and to note regions of interest for detailed image collection using the phone's screen that was connected to the remote controller. Following the overall image collection, detailed image collection was performed to capture all defects on each element. The pilot flew the aircraft as close as possible to the bridge elements and the regions of interest identified during the overall data collection. On the basis of the pilot's skill level, a distance of 5 ft to 6 ft was determined to be both safe and sufficiently close to capture necessary details. Then, high-resolution images of bridge elements from different angles were captured using the rotating gimbaled camera. The collected images and videos were stored in the memory card in JPEG and MP4 formats, respectively.

Chapter 5 Results

5.1 UAS Imaging

During overall image collection, 74 high-resolution images of the bridge were collected. The bridge elements containing defects were identified from the overall images visually, and more detailed images, a total of 260, containing defects such as cracking, efflorescence, spalling, and joint leakage were collected in the next step. Figures 5.1 through 5.3 present some of the defects identified from the detailed images. The total flight time per data collection was approximately 40 minutes, which was significantly less than the amount of time typically needed (several days) to collect data with the traditional inspection methods detailed in the introduction.



Figure 5.1 (a) Hairline shrinkage cracks on a column; (b) Hairline flexure cracks with efflorescence on the sides of boxes



Figure 5.2 (a) Sacking is falling off of a column; (b) Spalling at the bottom of the girder box



Figure 5.3 A failed joint seal leaking water

5.2 Image Processing

First, all RGB color format images were converted into grayscale images for further processing. The gray scale values were stretched to fill the entire gray-level range (0-255) by applying a mean filter to the high-resolution images. Figure 5.4 shows both the original and adjusted image histograms of a sample image. The grayscale adjustment resulted in a higher contrast, i.e., larger differences of pixel intensity, between the background and the cracks, making the cracks darker and the background brighter. However, the crack edges on the concrete surface were complex and could contain holes or material deficiencies. Contrast enhancement also highlighted these small deficiencies around the cracks. Therefore, the mean filter smoothed the gray values of the pixels, which discarded the unnecessary details of material deficiencies without affecting the shape and detail of the cracks. Through image enhancement and filtering, the contrast between the crack and background became more evident. As shown in figure 5.5, a 3D representation of the sample image after preprocessing, the gray levels of the crack were significantly lower than those of normal regions; therefore, a bottom hat transformation was performed to extract these dark regions of interest. However, some dark regions that were not cracks were classified in the same group as cracks at the end of the previous step. Therefore, threshold segmentation was applied to separate the cracks from those dark regions. However, at

the end of this step, some smaller regions and noise still remained in these images that were misidentified as cracks, which can be seen in the threshold segmentation image in figure 5.6. Therefore, morphological area opening was applied to remove these connected isolated small areas that were misidentified as cracks. Finally, the cracks were automatically detected and labeled on the images. The workflow used for crack detection is shown in figure 5.6. All of these processes were performed automatically on every high-resolution image collected with the UAS by coding for loops in MATLAB.

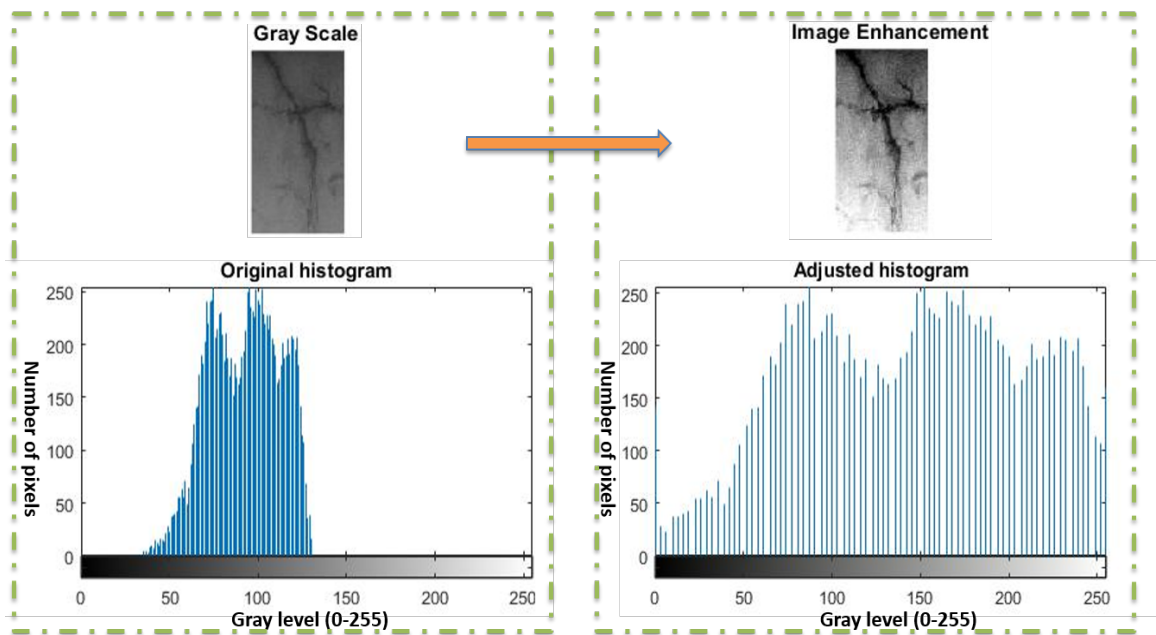


Figure 5.4 The original and adjusted histograms of a sample image

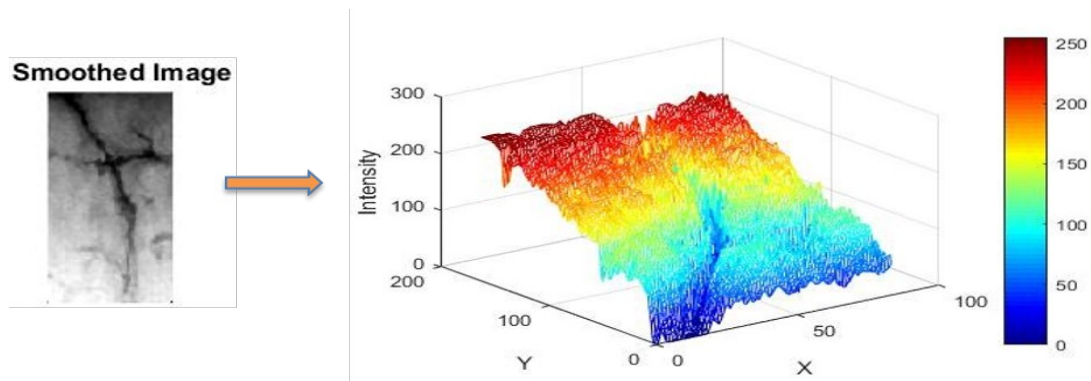


Figure 5.5 3D representation of the sample gray level image

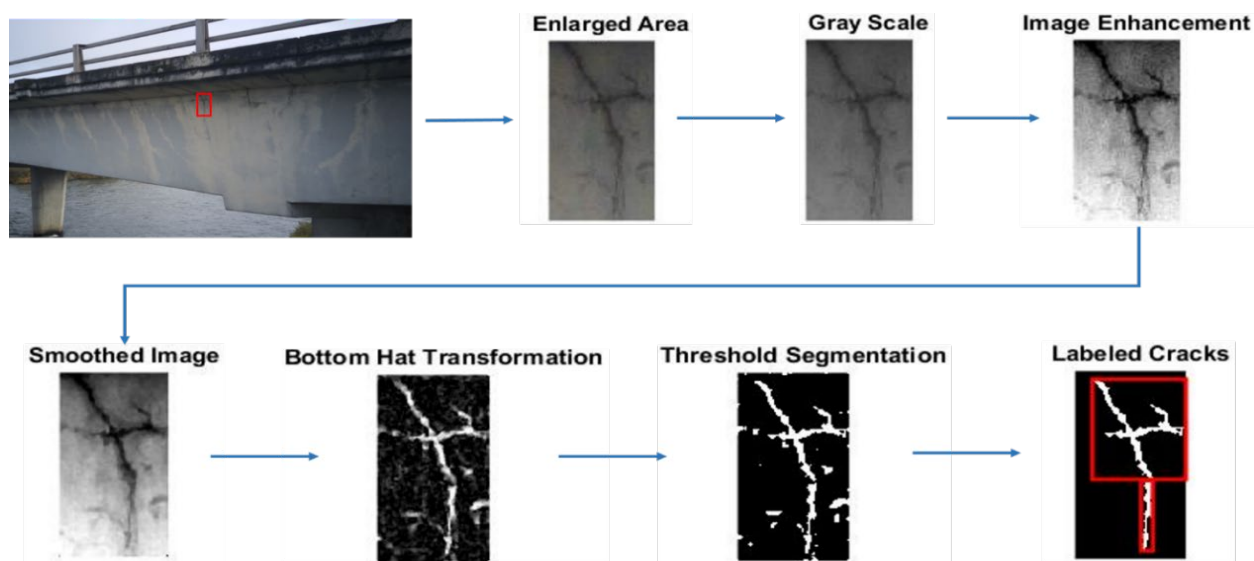


Figure 5.6 The processing results of a sample image using the proposed method

The detection results were analyzed by performing a visual comparison with the corresponding original images captured by the UAS. In order to validate whether all cracks observed visually were detected by the image processing algorithm automatically, precision and recall values were calculated and recorded for those 260 detailed, high-resolution images by using a 2x2 confusion matrix, which had two classes: Observation and Detection. It is important to note again that the purpose of capturing the overall images was to provide a background for indexing the detailed images. Therefore, the overall images were not processed in this step, as they did not contain the details of the defects/cracks. This is explained in more detail in the next chapter.

Four parameters were recorded for each image pair during visual comparison: 1) *true positive (TP)* represented the number of cracks observed in the original images that are actually detected by the algorithm; 2) *false negative (FN)* represented the number of cracks that were observed in original images but were not detected by the algorithm; 3) *false positive (FP)*

represented the number of cracks that were not observed in original images but were detected by the algorithm; and 4) *true negative (TN)* represented the number of cracks that were not observed in original images and were not detected by the algorithm. The true negative value was not available and was meaningless in this test because the cracks that were not observed in the original image were the black areas after detection. Furthermore, this did not affect the analysis results because the true negative value was not used for precision or recall calculations. The precision and recall values were calculated using TP, FP, and FN as follows:

$$Precision = \frac{TP}{TP+FP} \times 100\% \quad (5.1)$$

$$Recall = \frac{TP}{TP+FN} \times 100\% \quad (5.2)$$

where precision indicates the percentage of recognized cracks by the image processing algorithm that were actually observed in the image(s), while recall indicated the percentage of the cracks in the images that were actually recognized. A high recall rate would indicate that most cracks in the images were recognized, whereas a high precision rate would indicate how well the recognition was done without recognizing cracks that were not present in the images. Figure 5.7 shows an example image in which seven hairline flexure cracks were identified as cracks at the end of the image processing step. A visual comparison with the original image showed that all but one of the cracks in the image (false positive, labeled in red in figure 5.7(a)) were detected correctly. In this example, precision was 85.7 percent and recall was 100 percent, where TP = 6, FP = 1, and FN = 0. Precision and recall values were calculated for each pair of images used in the analysis, and the average precision value and recall value for the entire image set were 74.6 percent and 86.2 percent, respectively. The results showed that it was possible to determine the type, location, and orientation of defects by examining the detection results and the original

images. However, the precision and recall values indicated a need for developing classification and machine learning techniques that can improve defect/crack detection accuracy.



Figure 5.7 Crack detection results: (a) Original UAS image; (b) Detected and labeled cracks on the UAS image

5.3 Model Development, Data Integration, and Management

The procedure for integrating bridge inspection data is shown in figure 5.8. The 2D plans were obtained from Oregon DOT. The 3D bridge model was built on the basis of the 2D plans using the conceptual mass plug-in for Revit, as it enabled the creation of every bridge element in a 3D environment. It is important to note that the Revit software does not support/provide custom made elements for bridge design. On the other hand, the conceptual mass plug-in allowed the creation of custom families for bridge design, which could be categorized as deck, superstructure, and substructure. All families could be grouped together as one project to provide a visual representation of the entire bridge. Then the IFC text file that contained all the bridge elements could be exported to be used in the next step.

The IFC file could be opened in Notepad++, and the identified defect information in the previous step could be assigned to individual bridge elements by modifying the IFC text file. This was done by updating the line that corresponded to a specific bridge element with a string containing defect information for this particular element. This information could then be found in

the description field for the corresponding element when the IFC file was imported into the BIM vision software.

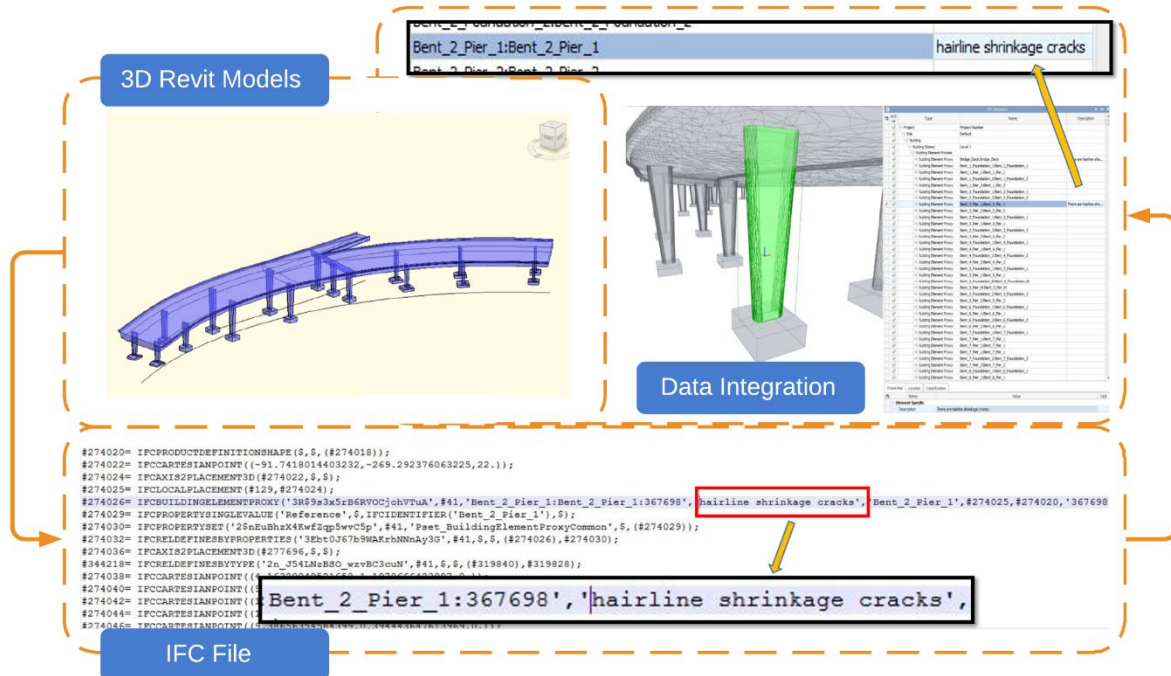


Figure 5.8 Procedure for integrating bridge inspection data

For data management, BIM 360 Glue was used to store the integrated model containing the defect information along with original UAS images and the historical inspection data (figure 5.9). With this program, different colors could be used to represent different severity levels based on the severity of the defect of a specific element, as in traditional inspection reports (figure 5.9). BIM 360 Glue would also enable access to the model along with the bridge inspection information that could be accessed and updated using mobile devices. This would enable effective and real-time communication between on-site personnel, e.g., inspectors and engineers, and decision makers in the office regarding inspection data.

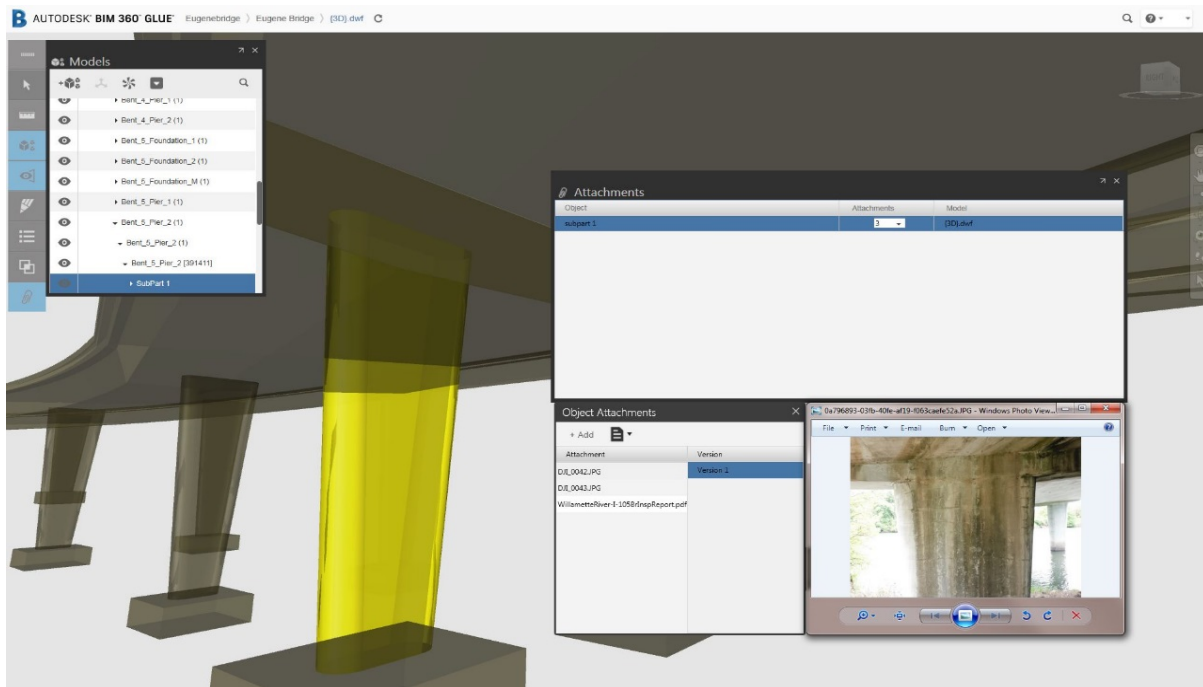


Figure 5.9 Bridge information management using Autodesk BIM 360 Glue

5.4 Efficiency Evaluation

The implementation results were compared with the most recent bridge inspection report obtained from ODOT to determine whether the shortcomings associated with current bridge inspection practice could be improved by using the proposed inspection framework. A rating scale from 1 to 4 was used to evaluate the framework's usefulness in improving each problem related to data collection, processing, and management. In the designated rating system, 1 = not useful at all, 2 = useful with limitations, 3 = useful, and 4 = very useful. An evaluation corresponding to the inherent problems discussed in the research background section are summarized in table 5.1. Note that this evaluation was done by the authors. In future work, a nationwide survey will be conducted to obtain feedback from bridge inspectors, engineers, and other state DOT personnel.

Table 5.1 Evaluation of the proposed bridge inspection and management framework

| Phases | Problems | Reasons the problems can or cannot be solved by the proposed framework | Rating (1-4) |
|-------------------|--|--|--------------|
| Bridge Inspection | Safety Risks | UAS has ability to capture high-resolution images within an arm's reach distance provides sufficient details of element conditions without requiring inspectors to climb or perform other dangerous activities. | 4 |
| | Costly | The amount spent on expensive equipment can be decreased; however, investments must be made in UASs, qualified pilots, and BIM software. | 3 |
| | Subjective | The ability to detect cracks automatically somewhat reduces the effects of inspectors' subjective judgement. However, the accuracy of the results is highly reliant on the images' coverage of the defects and the use of an appropriate algorithm. In addition, the image processing method used in the proposed framework cannot measure cracks; therefore, an inspector must later be able to touch the bridge to measure defects in the regions of interest. | 2 |
| | Time-consuming and Laborious | With the help of image processing algorithm, UAS imaging can automatically detect and label the defects (cracks) within the large number of images captured by the UAS, dramatically reducing the number of visits and time required to inspect each element. | 4 |
| Bridge Management | Does not work for entire life cycle | BrIM has the capacity to simplify the overall bridge life cycle and ensure that information is gained throughout each distinct phase (from concept design through operation/maintenance). However, this functionality is not very useful for existing structures, since most of these lack 3D models in their design and construction phases. | 4 |
| | Lack of Representation and Visualization of the data | BrIM data management allows the database with the models to provide direct representations and visualizations of the inspection information for specific elements. This, in turn, enables engineers to find valuable information faster and better understand how the condition of a structure has changed. | 4 |
| | Data Dispersion | | 4 |
| | Reports in Groups | BrIM enables condition information to be assigned to individual elements, reducing the possibility of overlooking the underlying reasons for individual element defects. | 3 |

Chapter 6 Discussion

Although the evaluation of the experiment showed that the shortcomings associated with the current bridge inspection practice and management could be mitigated by implementing the proposed framework, several challenges were associated with its implementation. In particular, the experiment enabled identification of two main challenges: crack detection accuracy and 3D bridge modeling, which are discussed below in detail.

6.1 Crack Detection Accuracy

The accuracy of crack detection is highly affected by how images are collected and processed. To detect all defects present on a bridge, full imaging coverage would be necessary. This would require both a highly skilled pilot and comprehensive flight route plans, especially when data were collecting from more complex bridge structures. Moreover, the experiment also revealed issues related to cracks covered by vegetation and dirt. Figure 6.1 shows how cracks covered with dirt were hard to see in the original images and are filtered following the threshold segmentation. Cleaning bridges before UAS data collection could help overcome this issue but would require additional staff and would involve extra costs.

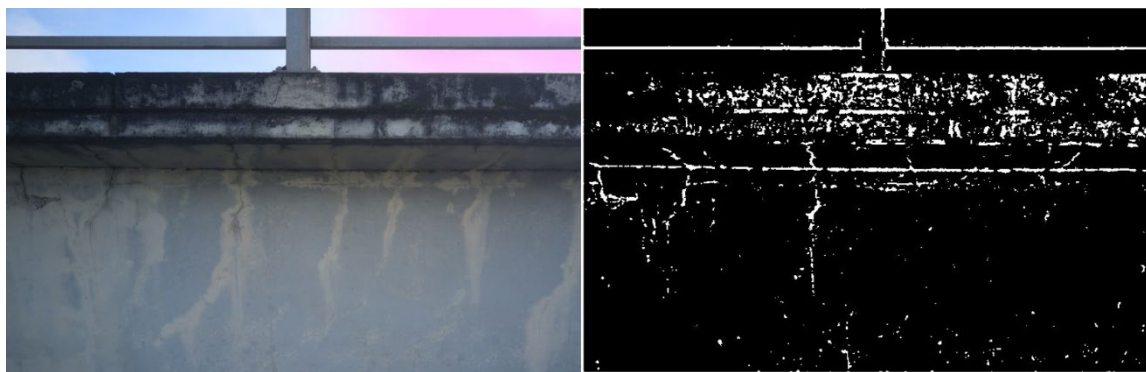


Figure 6.1 (a) Original image; (b) Corresponding binary image

Although cracks could be automatically detected by coding for loops in MATLAB, obvious edges of bridges and other objects (e.g., rivers) in overall images would affect the crack detection results adversely. The image processing algorithms used in this study analyzed the gray level of each pixel. However, edges are usually larger and more obvious than cracks. Therefore, it would be difficult to detect cracks without also detecting edges using the image processing method proposed in this study. For this reason, the detailed images had better crack detection results than overall images (detailed images did not contain as many edges and covered smaller areas around a defect/crack). This is why only detailed images were used for crack detection, and the precision and recall values were calculated by using the results obtained processing those detailed images. Figure 6.2 shows an example of crack detection results obtained by processing an overall image. In addition to the real cracks, the algorithm also identified the river, as well as the edges and railings of the bridge as cracks.

Perspective projection of the camera also affected the detection results, and to overcome this issue, advanced or customized UASs that could provide more accurate measurements of the distance between the camera center and target objects are recommended. This would also help avoid manual image cropping or parameter changes. To increase the accuracy of crack/defect detection, crack characteristics (e.g., shape or size) could be considered when classifier operators were developed for crack classification, which would be helpful for separating cracks and crack-like features, such as the edges and railings in figure 6.2. In addition, machine learning algorithms should be considered, as they would enable self-learning of the parameters and the features of interest, which would increase the efficiency and accuracy of the detection process. However, to obtain accurate results using machine learning algorithms, use of a large set of training images and accurate ground truth data would be vital.

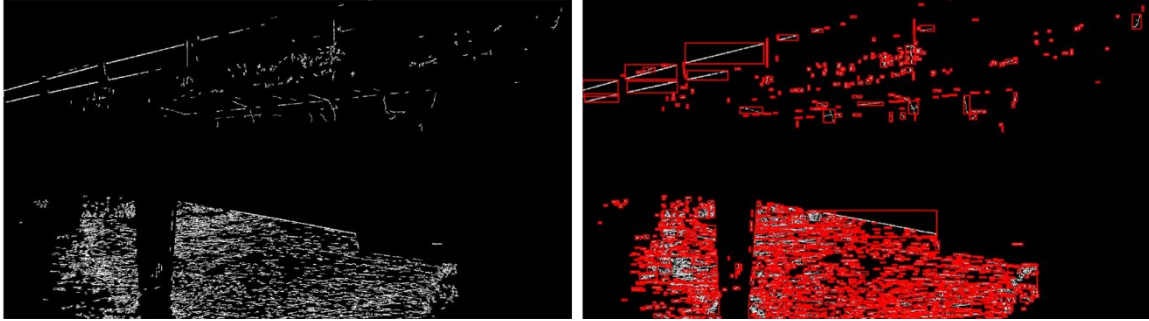


Figure 6.2 An example of a (a) binary image and (b) labeled cracks on the binary image

6.2 BrIM for Existing Bridges

BrIM is more widely adopted for the bridge design and construction phases than for bridge operations and maintenance (O&M) and management. The main obstacle limiting implementation in those phases for existing bridges has been the ability to create efficient and affordable models. Most existing bridges were built in the 20th century, and the available 2D as-built plans for those bridges contained limited information. Developing accurate BrIM models for tens of thousands of bridges based on available information would be difficult and laborious. Moreover, unlike designing a bridge, which involves detailed standards concerning levels of detail, there are no uniform standards for BrIM modeling for the O&M phase (i.e., as-built BrIM that can be used during O&M). This makes managing and sharing models across agencies difficult.

In this study, the BrIM model was developed in the conceptual mass environment within Revit. Although this environment does not provide components unique to bridges, the primary bridge elements (National Bridge Elements (NBEs)), which are critical for bridge inspection, have been successfully built through the creation of geometric forms. The developed BrIM model can be easily enhanced and enriched to support detailed structural assessment if infrastructure packages were available in Revit or other platforms. Though the developed BrIM model in this study has limited details, it includes major BrIM attributes that could help fill the

gap between 2D as-built bridge drawings and comprehensive models for existing bridges. The relatively simple process to develop models using conceptual mass, and its attributes for visually representing bridges and housing all bridge information in a single model, could increase stakeholder' acceptance of BrIM use for O&M phases.

Chapter 7 Conclusions and Recommendations

7.1 Conclusions

Bridge inspection is a critical task for providing all Americans with a safe and reliable infrastructure. However, current bridge inspection practices are considered inefficient, as they are time-consuming, expensive, unsafe, and subjective. In this study, a novel framework was proposed to mitigate some of the problems involved in current bridge inspection and management practice by implementing BrIM and camera-based UASs. The proposed framework was implemented on an existing bridge. A detailed description of imaging plans, data processing and analysis, and integration of defect information into the BrIM are provided in the illustrative case study. The results obtained from the case study verified that high-resolution images captured by a UAS enabled visual identification of different types of defects, and detection of cracks automatically using computer vision algorithms. The results also verified that the use of BrIM enabled the assignment of defect information on individual model elements to manage all bridge data in a single model across the bridge life cycle, has the potential to reduce the number of site visits by eliminating data re-entry with the assistance of cloud computing technology. The proposed framework showed potential to address some of the problems associated with current bridge inspection and management practices in terms of safety, cost-efficiency, and effectiveness.

7.2 Recommendations for Future Work

A number of limitations in this study need to be noted. First, the proposed framework focuses on accelerating the process to find the locations of defects on a given bridge and understanding how to integrate this information with bridge information models (at the object level) for better inspection data management. The framework does not support automatic

measurement of the length and width of cracks and other defects, which is critical in inspection work. Second, the framework was evaluated to determine whether the proposed framework could solve existing problems in current bridge inspection and management practices. However, it did not consider whether those problems are equally important. For example, problems associated with subjectivity and safety risks should be prioritized over cost-related issues. Therefore, the weighting of different problems could affect the ratings when the framework is evaluated and needs to be considered for obtaining a more accurate evaluation. Furthermore, the ratings used in the evaluation were assigned by the authors on the basis of the results of the implementation, which may not have been accurate because of the authors' limited experience. In future work, the professional opinions of bridge inspectors working for state DOTs will be obtained through a nationwide survey to improve the quality and persuasiveness of the evaluation.

Several other challenges associated with the implementation of this framework in practice should be addressed in future work. Recommendations for future work are as follows:

- Comprehensive UAV flight planning prior to data collection is highly recommended in order to provide consistent images and to reduce manual work in subsequent image processing, especially when dealing with complex and large-scale bridges.
- To increase crack detection accuracy, it would be necessary to develop appropriate classification operators to separate real cracks from similar features. Machine learning algorithms could be used to train the classifier on a large database of images containing different types of cracks.
- To determine the severity of defects/cracks automatically, which would significantly enhance the effectiveness of the proposed framework, computer vision-based measurement algorithms should also be developed.

- The future research should focus on development of more accurate bridge information models with detailed parametric information and on identification of model development specifications for existing bridges that satisfy stakeholders' demands.

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