Bridge Inspection Using Bridge Information Modeling (BrIM) and Unmanned Aerial System (UAS)

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Abstract

Bridge inspection is a critical task that is needed to monitor bridge quality and serviceability. Previous studies indicate that road network and bridges in the U.S. are not of high quality and poorly maintained for decades, and the current manual inspection routine is expensive, time-consuming, hazardous, and subjective. Moreover, current Bridge Management Systems (BMS) may not coordinate management of all phases of the bridge life cycle. Also, the dispersed inspection data drastically reduces the effectiveness of the system. Therefore, there is a need to identify cost-efficient and productive ways to inspect and manage our bridges. The objective of this study is to develop a novel framework for bridge inspections and management. The framework implements Bridge Information Modeling (BrIM) and Unmanned Aerial Systems (UASs) technologies in an integrated manner to solve the issues associated with current manual bridge inspection and management practice. The proposed framework was implemented using data collected from an existing bridge located in Eugene, Oregon. Different types of defects were identified automatically using computer vision algorithms from the digital images captured by the UAS. These defects were assigned to individual BrIM elements. BrIM was used as the central database to store the 3D bridge model and 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: (1) provides a systematic approach for accurately documenting the structural condition assessment data, (2) reduces the number of site visits and eliminates potential errors resulting from data transcription, and (3) enables a more efficient, cost-effective and safer bridge inspection process.

Keywords

Building information modeling (BIM) • Bridge information modeling (BrIM) • Unmanned aerial systems (UASs) • Crack detection

74.1 Introduction

The strength and growth of the U.S. economy, and the quality of life of all Americans, depend, in part, on the quality, sustainability, and condition of its infrastructure such as road network and bridges. However, previous studies indicate road network and bridges in the U.S. are not of high quality and poorly maintained for decades [9]. In August 2007, the I-35 W Mississippi River Bridge suddenly collapsed during evening rush hour. The reason behind the collapse was mainly attributed to a design flaw of the gusset plates and vertical clearance. Because of this structural failure and bridge collapse, 13 people were killed and 145 were injured. Similarly, in May 2013, I-5 Skagit Bridge near Seattle collapsed into the river after being struck by an oversized truck. Three people were seriously injured and the incident affected an average of 71,000 drivers who used this bridge to commute daily. Most recently, in March 2018, a pedestrian bridge that connects Florida International University with a neighboring city was also collapsed due to similar circumstances killing six people and injuring more than

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a dozen people [23]. These catastrophes raised the public's attention on the status of the nation's bridges and their maintenance operations. The most recent Infrastructure Report Card that was released by American Society of Civil Engineers (ASCE) reported an overall C+ (mediocre) grade for bridges. Forty percent of U.S. bridges are over 50 years old [4], exceeding their designed life span. In addition, 9.1% of the bridges were classified as structurally deficient in 2016 [4]. Although, structurally deficient bridges do not necessarily indicate that those bridges are unsafe or likely to collapse, it does mean that their critical carrying elements are in poor condition due to deterioration or partial damage. This necessitates frequent monitoring and inspection to eliminate possible and potential structural failure or collapse. However, the back-logged budget for bridge rehabilitation has reached $123 billion [4]. In summary, the U.S.'s aging and deteriorated road and bridge systems and limited budget emphasize the need to develop an efficient and cost-effective bridge inspection process that can reduce or prevent the possibility of structural collapse of bridges.

74.2 Background

74.2.1 Current Bridge Inspection Practice and Problems Identified

Bridge inspections are critical for monitoring bridge quality and serviceability as they provide detailed information regarding the structural stability of bridges. The Federal Highway Administration (FHWA) requires that all states perform biennial routine inspections for each bridge [1] and recommends an inspection at least once a year for those bridges that are rated as structurally deficient [4]. However, current bridge inspection is mainly based on visual and paper-based practices as it requires an inspector correctly identify the type, location and severity of each bridge element, and manually record the damages by using checklists, taking notes, and drawing sketches while on site. They document all this data by using standard inspection reports and update it into Bridge Management Systems (BMSs) after they go back to their office. The system enables bridge engineers to access and compare with previous inspection results, and identify any repair/rehabilitation/maintenance needs.

There are several shortcomings associated with current visual and paper-based inspection and data management practices. First, inspectors might be exposed to safety risks while performing the evaluation, especially when reaching areas with limited accessibility. Second, equipment used for inspection such as elevating platforms and scaffolding are expensive and can disrupt the flow of traffic. Third, the evaluation process cannot be objectively performed and may be impacted by the experience of the inspector, which may affect the accuracy of the inspection results [7]. Fourth, the process is expensive and laborious. Moreover, current BMSs can be inefficient due to several reasons: (1) stand-alone BMS does not satisfy the increasing need to coordinate management of all phases for entire bridge life cycle [19, 21]; (2) current BMSs provide a 2D database, i.e. does not enable 3D visualization of the data [8]; (3) large amount of inspection data is input from a variety of sources, which can possibly lead to an issue of data dispersion [10]; and (4) the condition of similar types of elements are grouped together to report defects, which might hide the inner reasons for the defects on specific elements [8]. Based on the aforementioned discussion, previous studies have proposed several ideas implementing various technologies to improve bridge inspection and management practices.

74.2.2 Technology Used in Data Acquisition and Processing for Inspection

To overcome the inherent weaknesses in visual bridge inspection processes, previous studies proposed implementation of several non-destructive technologies. Ground Penetrating Radar (GPR) has been used for concrete and masonry bridge inspection, especially for deck condition assessments [2], and has shown high capability to detect size and location of concrete delamination area of bridge decks compared to visual inspection methods [20]. However, the quantitative method to analyze the GPR profile overlook some of the important information in the profile, such as change in reinforcing bar spacing slab thickness [22]. Infrared (IR) thermography is another non-destructive technique for detecting subsurface defects that is available for concrete bridge inspection and evaluation [2]. Being inexpensive and ease of use are the two main advantages of this technology. However, IR Thermography analysis maybe affected by many factors, such as the surface condition and the environment condition [26]. Besides subsurface defects and deteriorations, surface defects such as cracks are important indicators of structure's health and also need to be monitored. Terrestrial Laser Scanners (TLS), which are known for their capability to rapidly obtain accurate surface information of structures and present this information in the form of three-dimensional (3D) high-dense point clouds, have been used in bridge inspection as well. Thruong-Hong et al. proposed a framework that utilized TLS technology in bridge inspections for deformation measurements, damage detection, and reconstruction of 3D models. They concluded that TLS can provide sufficient information for structural condition assessment [24]. That being said, although TLS can produce high resolution and accurate output, the large file sizes and long processing times are the primary barriers of its wider adoption in the Architectural, Engineering and Construction, and Facilities Management (AEC-FM) industry. Turkan et al. [25] developed a novel adaptive Wavelet Neural Networks (WNN) based approach to overcome the drawback associated with using TLS technology for bridge inspections. The proposed adaptive WNN-based approach detects concrete cracks from low-resolution TLS point clouds, which enables 3D point cloud data to be processed quickly and detect cracks automatically. However, even with that, TLS is still not the optimal option from an economic standpoint. In [18], it was shown that the cost for TLS without annual maintenance tend to be six times or more expensive than using photogrammetry [18].

The utilization of UAS to collect aerial images has recently received significant attention in the AEC-FM industry due to its safety benefits, ease of use, mobility, and cost-effectiveness [14]. UAS is considered one of the most trending engineering tools in infrastructure inspection and evaluation. It is frequently used in high risk situations to isolate inspectors from potential workplace hazards. Images collected by UAS are of high resolution and comparable to conventional bridge inspection results [12, 17], especially with respect to identifying potential defects in bridge connections, concrete spalling, and cracks [12]. In addition, using UASs for bridge inspection has little, if any, impact on traffic flow. Furthermore, it eliminates the need to use large equipment, accelerates the inspection process, and provides opportunity to use nondestructive techniques for crack detection [16]. However, due to the low weight of UAS, the quality of images is sensitive to environmental factors such as lighting conditions and wind speed and direction [13], which may be the major hindrance for implementing UAS for condition assessment of civil structures.

74.2.3 Technology Used in Data Management for Inspection

Building information modeling (BIM) is a revolutionary development that has rapidly changed the AEC-FM industry. BIM can be considered both as a technology and as a process that embed all information needed for constructing a facility in a single, virtual 3D model. This 3D model can be transferred and shared with other project teams [5, 6]. BIM enhances project team communication and collaboration through the use of Industry Foundation Classes (IFC), a neutral file format that improves interoperability among applications with different file formats from design to operation and maintenance phases [11]. BrIM is the acronym used for BIM when it is applied to bridge projects. BrIM enables integration of defect information with each component and visualization of bridge conditions. This capability can help overcome the shortcomings in existing paper-based inspection and bridge data management practices. A framework that integrates inspected structural data with a 3D bridge information model was proposed by DiBernardo [10]. Following this work, Al-Shalabi et al. [3] proposed a 3D BrIM enabled inspection framework that implements mobile devices, and cloud computing. In this framework, information regarding bridge elements can easily be accessed using mobile devices during inspection, and inspection data such as crack type, size etc. can be added to the database easily. This framework was tested by Iowa DOT inspectors, who confirmed the benefits of implementing BrIM for bridge inspections. However, there are only a few studies focused on using BrIM for data management. In addition, there exists a gap between onsite inspection data collection for existing bridges and how to apply BrIM to integrate inspection data with virtual models for bridge management.

Previous studies demonstrated various technologies that can be utilized to improve bridge inspection and management practice, it is clear that there is a need for a systematic approach for collecting and documenting bridge inspection data. By building on the framework developed in [3], this study proposes a bridge structural inspection framework combining UAS and BrIM technologies. UAS enable safer and rapid collection of visual bridge inspection data in the form of digital images; whereas, BrIM enable storing all bridge data, including its drawings and 3D models, inspection notes, images, and other related data, in a central object-oriented database that can be accessed both from the office and in the field. This environment combines a 3D representation of the infrastructure and allows the integration of inspection data, such as the presence of damage, type of damage, severity of damage, and previous maintenance decisions.

74.3 Research Methodology

The proposed bridge inspection framework (Fig. 74.1) has three major components: (1) 3D modeling; (2) UAV imaging and processing, and (3) data integration and management.

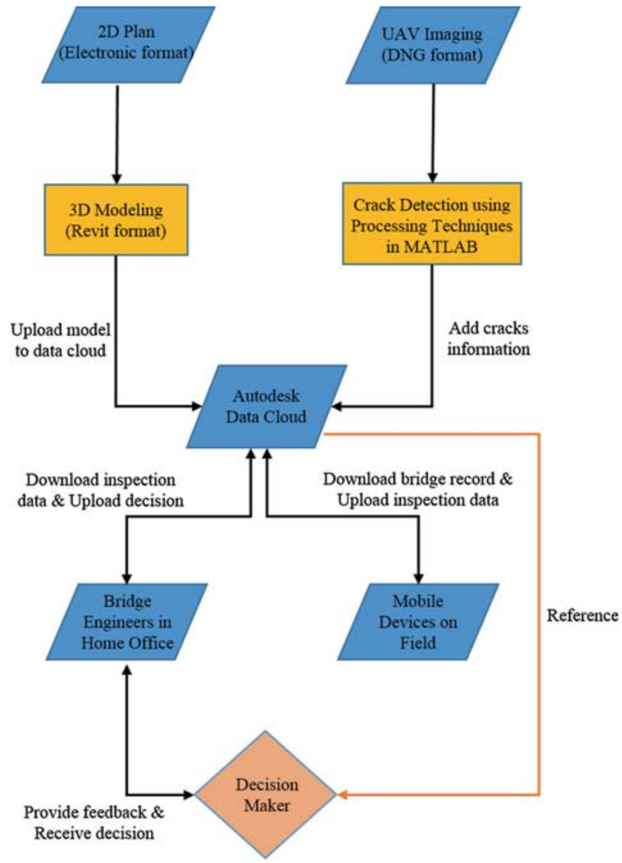

Fig. 74.1 Proposed bridge inspection framework

First, 3D BrIM model of the bridge is built at element-level using conceptual mass in Revit based on the 2D as-built plans. Concurrently, images of both the overall site and bridge elements were captured using a UAS. MATLAB Image processing tools were implemented to detect cracks automatically. From the processed images, crack information such as type, location, and orientation are assigned to individual 3D BrIM elements and uploaded to Autodesk data cloud. The 3D BrIM model integrated with images from the UAS and crack information would enable inspectors quickly locate the region that has defects. In addition, the data cloud can be accessed and updated both from the site and home office, enabling all stakeholders have access to inspection data simultaneously.

For image processing, the following steps were performed using MATLAB image processing tools [15]: (1) colored images were converted to gray-scale images for further processing; (2) contrast adjustment was used for image enhancement; (3) median filter was applied to reduce noise in images; (4) bottom-hat morphological operations were applied to extract dark regions as objects from the background; (5) threshold segmentation was applied to separate cracks from the obtained objects, which results in binary images; (6) morphological area opening was applied to reduce the connected objects, and labeled cracks using bounding boxes based on region properties.

74.4 Data Collection and Preliminary Results

The proposed framework was tested on an existing bridge located on highway I-105 spanning over the Willamette River in Eugene, Oregon, which was constructed in 1967. Its total length and width are 844 and 81.17 ft respectively and has been rated as structurally deficient in the latest available inspection report, mainly due to its poor deck condition.

Fig. 74.2 Aircraft, controller, and pilot

74.4.1 UAS Data Collection

UAS flights were conducted on December 1 and 7, 2017. DJI Mavic Pro Quadcopter with a gimballed camera was used to collect 4 K video and 12-megapixel photography. The aircraft was controlled by the pilot using a remote controller connected to an Android phone (Fig. 74.2). Manual flight mode was used in this study. The pilot flew the aircraft along both sides of the studied bridge and found 5-6 feet as a safe distance while capturing high quality images. The second step of the data collection involved the pilot rotating the gimballed camera to capture high-resolution images of bridge elements from different angles. The interval of hovers was also controlled by the pilot to ensure enough overlap between the images. Real-time images and videos were displayed on the connected phone and the captured images and videos were stored in the memory card in JPEG and MP4 formats respectively.

74.4.2 Preliminary Results

UAS Imaging. 334 high resolution images were successfully collected from the studied bridge. The flight time for each data collection was about 30 min, which drastically shortens the time inspectors spent on site compared to traditional inspection practice. 260 high-resolution images successfully captured defects such as cracking, efflorescence, spalling, and joint leakage. Sample images show some of these defects (Fig. 74.3).

Crack Detection. All original images from UAS were converted to gray-scale images for image processing. The workflow and the results for sample crack detection are shown in Fig. 74.4. After adjusting image intensity values, the contrast between the background and cracks were improved; cracks became darker and the background became brighter. Also, contrast enhancement made material deficiencies around cracks clearer. Next, mean filter was applied to remove Salt and Pepper noise, which smoothed the gray value of pixels while preserving the edges and details of the cracks. Since cracks have lower gray values, bottom hat transformation was performed to enhance dark regions of interest, i.e. cracks. However,

Fig. 74.3 Sample images of defects: **a** cracking with efflorescence on the side of the box **b** spalling area underside the box **c** rust staining on the concrete column

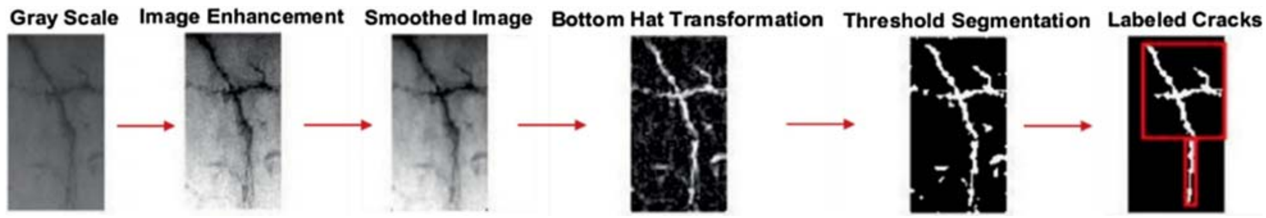

Fig. 74.4 Sample detection results of the workflow

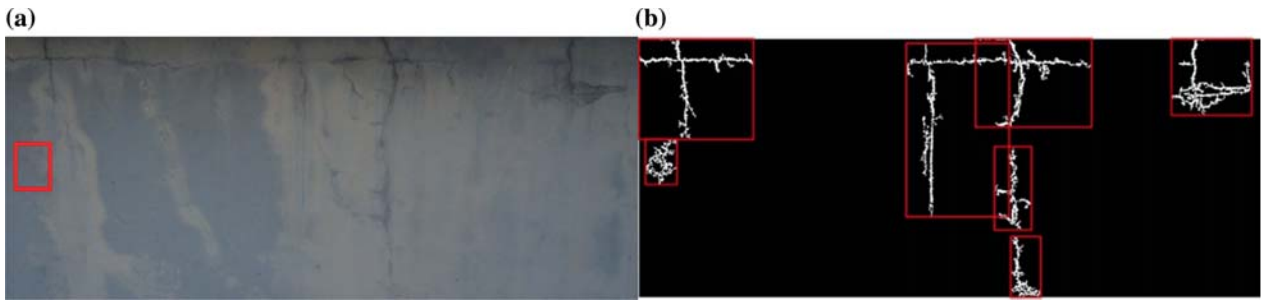

Fig. 74.5 Example of results: **a** original image that was captured by UAS **b** labeled cracks that detected based on the workflow

some dark regions except cracks were also enhanced and extracted after threshold segmentation. Morphological area opening was applied to remove the connected isolated small objects. As a last step, the cracks were labeled on images.

Detection results of an example image revealed that seven hairline flexure objects were detected automatically as cracks (Fig. 74.5b). However, a visual comparison revealed that one crack was falsely detected (false positive) (labeled in Fig. 74.5a). This indicates the need for future research focus on improving classification and machine-learning techniques to improve the detection accuracy.

Data Integration and Management. The 3D bridge model was built using conceptual mass in Revit (Fig. 74.6a). The conceptual massing environment is suitable for modeling irregular shapes that is good for modeling curved bridges. Although the massing environment does not provide shapes that are unique for a bridge, bridge elements can be built by creating custom families. It provides a visual representation of the bridge and enables storing all inspection data in a single model.

For data integration, BrIM model is converted to IFC format (Fig. 74.6b), a neutral file format that facilitates data exchange between different software. Cracks or defects identified during the crack detection step as well as all UAS images can be assigned to individual bridge elements by modifying the IFC file. This is done by updating the line in the IFC text file that represents the specific bridge element with a string containing crack information for that particular element. This information appears in the description field for the specific element when IFC file is imported into Version 2.18.11 of BIM vision software (Fig. 74.6c). For data management, the integrated model along with original UAS images and previous inspection information are uploaded to Autodesk data cloud (BIM 360 Glue was used in this study). The images of individual elements can be linked to that model element as well. Based on the condition of a specific element, different colors are used to represent different condition states (e.g. green: good condition, red: critical condition). This data cloud can be accessed and updated from both the worksite and home office simultaneously, enabling critical, timely decision making.

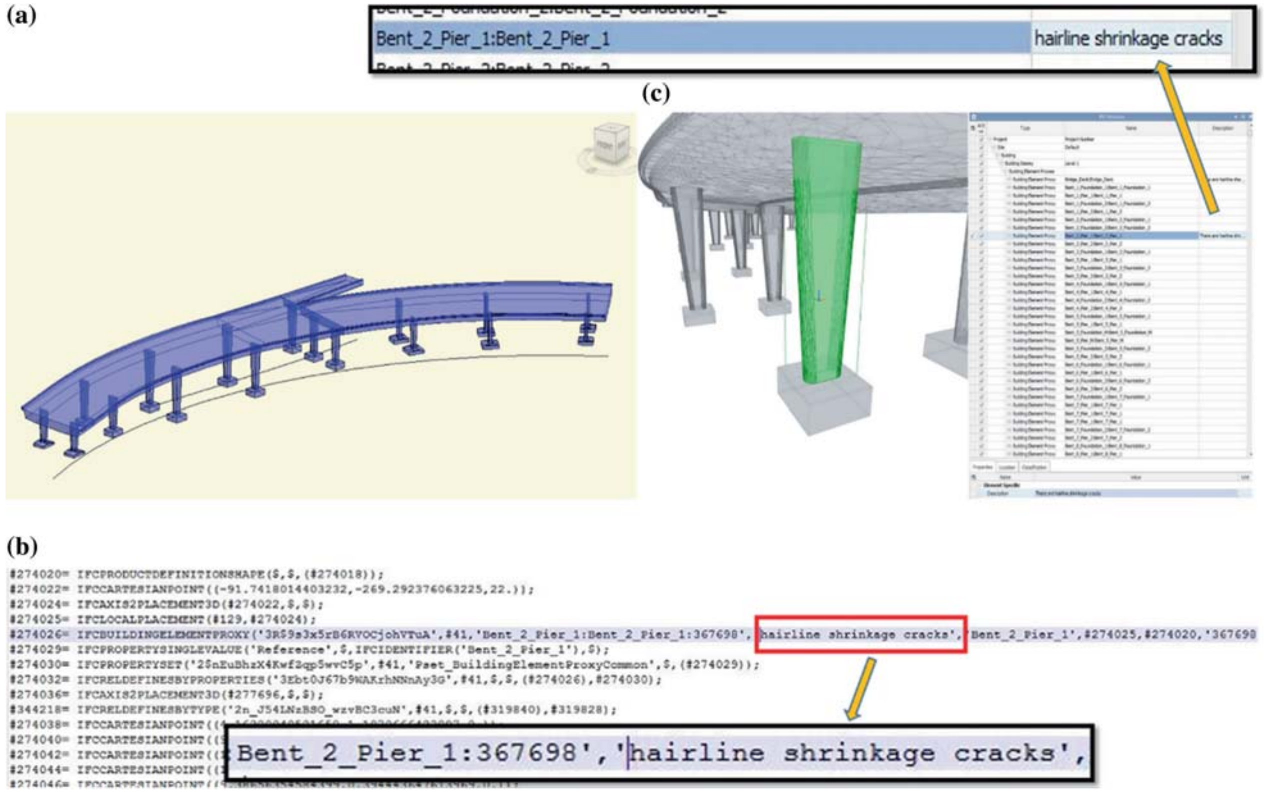

Fig. 74.6 **a** 3D BrIM model in Revit **b** sample IFC text file with crack information **c** integrated BrIM model opened in BIM Vision

74.5 Conclusions and Future Work

Although bridge inspection is a critical task needed to monitor bridge quality and serviceability, current bridge inspection practice is considered inefficient mainly due to its time-consuming, costly, unsafe, and subjective nature. Moreover, current BMS do not satisfy the increasing need to coordinate management of all phases for entire bridge life cycle. Also, the dispersed inspection data drastically reduces the effectiveness of the system. This study proposed a novel framework that uses BrIM and UAS data to improve current bridge inspection practice. This study proposed a novel framework that implements BrIM and UAS data to improve current bridge inspection and management practice. By testing the proposed framework on an existing bridge, the results verified that high-resolution images captured by UAS enable identification of different types of defects, and detect cracks automatically using computer vision algorithms. Furthermore, the results also verified that the use of BrIM enable assigning defects information on individual model elements, manage all bridge data in a single model, and has the potential to reduce the number of visits while eliminating data re-entry with the assist of cloud computing. In addition, the proposed framework has the potential to improve the current inspection practice in terms of safety, cost-efficiency, and effectiveness. Future research will focus on assessing the practicality of the proposed framework through a survey among state DOTs, focusing on Region 10 DOTs (Alaska, Idaho, Oregon and Washington). Furthermore, to increase crack detection accuracy, it is necessary to develop appropriate classification operators to separate real cracks from similar objects. Machine learning algorithms will be investigated to train the classifier on a large database of images containing different types of cracks.

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