

Challenges of bridge maintenance inspection

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Abstract:

Bridges are amongst the largest, most expensive and complex structures, which makes them crucial and valuable transportation asset for modern infrastructure. Bridge inspection is a crucial component of monitoring and maintaining these complex structures. It provides a safety assessment and condition documentation on a regular basis, noting maintenance actions needed to counteract defects like cracks, corrosion and spalling. This paper presents the challenges with existing bridge maintenance inspection as well as an overview on proposed methods to overcome these challenges by automating inspection using computer vision methods. As a conclusion, existing methods for automated bridge inspection are able to detect one class of damage type based on images. A multiclass approach that also considers the 3D geometry, as inspectors do, is missing.

Keywords: Bridge inspection, synthesis, automated damage detection.

1. INTRODUCTION

Transportation authorities undertake enormous efforts to maintain transportation networks and aging bridges despite increases in traffic. The US Federal Highway Administration (FHWA) spent \$12.8 billion in 2013 for bridge maintenance (ASCE, 2013). England spent £4 billion in 2012-13 for maintaining the road network (Department for Transport and Highways Agency, 2014). At the same time, there is an urgent need for greater monetary resources to ensure reliable structural inspection and proper bridge maintenance. The FHWA estimates the required maintenance investment to be \$20.5 billion annually to eliminate the deficient bridge backlog by 2028. Currently, only \$12.8 billion are spent (ASCE, 2013). McKinsey estimates the funding gap for road and rail in the UK to be around £100 billion between 2010 and 2030 (McKinsey&Company, 2011). In contrast, the UK Department for Transport proposed cutting annual road maintenance budgets by £1.2 billion (Department for Transport and Highways Agency, 2014).

Strategies have been developed to prioritize among various maintenance needs with the objective of maximizing value for money (London Bridges Engineering Group, 2008). Prioritization processes generally include the relevance of a structure for a road network, and its condition for assessing safety risks for bridge users and impact on the lifecycle of a structure.

Bridges are complex structures that are constantly exposed to adversities like changing temperatures, moisture, and dynamic loading. This makes them difficult to inspect. A comprehensive study on the reliability of manual inspection has identified significant drawbacks regarding completeness and objectivity (Phares et al., 2004). One task analyzed in this study was to assign condition ratings to primary bridge components. Inspectors gave, on average, four-to-five different condition ratings. Assuming the reference condition rating to be correct, 58% of individual ratings were assigned incorrectly (Moore et al., 2001).

Additionally, protective equipment and mobile elevating work platforms have to be used in order to inspect specific areas such as the underside. The use of protective equipment can be cumbersome and the associated risk is considerable. If falling from a height of 3.4 meters or more, the chance of survival is only 50%, making this the second biggest risk factor for fatal work accidents (Gaus, 2012).

The following sections provide a synthesis of established bridge inspection methods, and a review of existing methods for automated bridge inspection. This work concentrates on visual inspection, as this is the predominant inspection type (Hampshire County Council, 2015).

2. ESTABLISHED BRIDGE INSPECTION SCHEME

International transportation and bridge authorities exchange best practices and recommendations leading to comparable bridge inspection standards worldwide. In general, there are three objectives: (1) confirm asset safety for public use, (2) provide damage information and identify maintenance needs, and (3) compile, verify and maintain inventory data for long-term bridge management.

2.1 Level and Frequency

Different inspection levels are defined to fulfil the purpose (London Underground, 2014). They mainly differ in frequency, accuracy and duration. The lowest tier and most often performed inspection is the security inspection, which is typically done every year. It is conducted from a slow driving car and focuses on detecting obvious defects and damage caused by accidents, over-height vehicle impacts, or vandalism. The second level of inspection is the general inspection, which is done every two years. This inspection collects physical condition data for all visible elements. It is performed by an inspector at visible ranges and requires little traffic control. The third level of inspection is a principal inspection, which is performed every five or six years. It is an in-depth inspection that requires close examination of elements within touching distance, and use of service tools and instruments like a hammer, paint thickness analyzer, or an instrument to measure crack width. These three inspection types are performed in an alternating fixed scheme (Hampshire County Council, 2015). Severe findings might require a more rigid scheme. Additional inspections are performed on an irregular basis, or as required. A special inspection provides detailed information on a particular element, damage, or area. An acceptance inspection is performed upon completion of a bridge, which primarily aims to exchange information and agree on current status for approval of a construction contract. Some countries such as Denmark and France have a flexible inspection scheme that allows an inspector to decide on the duration until the next inspection based on inspector experience and imminent deterioration of a structure (U.S. Department of Transportation, 2008).

2.2 Inspection Personnel and Qualification

Inspection is commonly performed by a team of transportation authority personnel or external service providers. An international comparison shows differences in training requirements. To date, the UK has no formal inspector training. No aptitude tests are carried out to check if inspectors suffer from fear of height, color blindness, or debility of sight (Moore et al., 2001). To address this, the UK Bridges Board developed a Bridge Inspector Competence Scheme, which will soon become the mandatory inspector qualification scheme in the UK (Department of Transport, 2012). In contrast, Finland has a more rigorous scheme. Bridge inspectors are tested annually in a one-day session that includes two example inspections, a discussion of inspection results, and a written test that must be passed. To assure quality, three inspectors examine an identical bridge independently. Results are reviewed and checked for consistency. If results differ substantially, inspectors can lose their certification (U.S. Department of Transportation, 2008).

2.3 Reporting and Bridge Management Systems

Software such as Bridge Management System (BMS) is typically used for managing inspection reports. It allows storage, manipulation and management of bridge data, and supports the engineering, asset management, and resource planning processes (Roads Liaison Group, 2005). On-site data can be collected using electronic handheld devices. Electronic inspection forms consist of dropdown fields that enable an inspector to quickly input data, which reduces mistakes and office rework. Most systems are either developed internally by a responsible engineer in the authorities, or bought and adapted to specific needs (The IABMAS Bridge Management Committee, 2014). Common systems for bridge management are BridgeStation or AMX in the UK. In the USA a well-known BMS called Pontis is now known as AASHTOWare Bridge and has been implemented into a wider management framework. An adapted version is used in other countries (The IABMAS Bridge Management Committee, 2014). Bridge management systems are developed to support an objective decision process based on inspection data. Additional features vary within different systems. Some additional features are, for example, calculation of a bridge condition index (London Bridges Engineering Group, 2010) or maintenance prioritization (London Bridges Engineering Group, 2008). Bridge management systems play a decisive role in modern asset management.

2.4 Damage Assessment

Several different types of damage have to be identified during an inspection. The U.S. Department of Transportation (U.S. Department of Transportation, 2012) defines 28 concrete damage types to be distinguished during inspection. Some defects can be detected visually (e.g. cracks, spalling, scaling), while others need additional tools (e.g. delamination) or even laboratory testing (e.g. alkali-silica reaction). Once a defect has been detected, the cause must be identified. For example, a crack can be due to normal shrinkage, or it could indicate a more serious structural concern. An inspector assesses each defect based on professional experience, physical properties (e.g. location, orientation, size), and progression since last inspection. A book with defect images and their respective ratings is used as a reference. Recording the physical properties of each defect enables monitoring of progression in future inspections. In the case of a crack, its properties are typically length, width, and orientation. However, no precise formal definition exists for how to measure these properties. Clearly, this leads to differing and subjective measurements.

3. AUTOMATED VISUAL INSPECTION

An automated visual inspection can be divided into several steps. Data acquisition is the process of capturing information of a bridge. This includes imaging sensor technology, actuating elements to move a sensor, and data reduction to merge data from multiple sensors to a single dataset. Damage localization divides data into critical and non-critical areas. Damage feature extraction tags a defect location with the damage type, and extracts essential information such as height, width, and length. Damage assessment analyses the impact of defects to a structure and its material. Finally, data handling organizes information retrieved for documentation, review, and reuse.

3.1 Data acquisition

(1) Sensors

Using a digital camera, a large number of images are needed to record all relevant parts of a bridge. A direct merging of the images is not possible, and precise camera movement between two shots is necessary to stitch images together. This can either be done by accurately controlling the camera position manually using a camera rig or automatically using a robot such as GigaPan (McRobbie, 2009). Alternatively, it can be done by extracting distinct correspondences within different pictures to reconstruct camera movement (Szeliski, 2006). Controlling camera position is completely independent from image content, which enables stitching of images without any distinct features. However, accurate positioning is labor-intensive and imprecise. Using image correspondences requires overlap between images so that a sufficient number of independent correspondences can be identified. For pictures with no features (e.g. faultless concrete) or repetitive structure (e.g. girders), extraction of correspondences might be impossible or error-prone.

Light detection and ranging (Lidar) is a remote sensing technology used to build a 3D point cloud. The distance to a surface is measured resulting in dense collections of single points in 3D space with x, y, z coordinates. An integrated camera collects additional color and intensity information for each point. The result is a colored 3D point cloud. Modern Lidar devices obtain high precision point clouds (± 2 mm) in a wide field of view (130m distance, 300/360 degree vertically/horizontally (Trimble, 2014)). To record a bridge, a Lidar device is set to different positions such that every surface point is visible from at least one scanner position. Reference points, or targets, are used to find correspondences. Iterative Closest Point (ICP) is used to merge the data from separate scans into a single coherent point cloud. This method starts from an initial transformation estimate and continues to find point correspondences between point clouds (Guldur & Hajjar, 2014). Guldur and Hajjar (Guldur & Hajjar, 2014) identify surface reflectance as the most important source of error. This error, along with occlusion or insufficient access, leads to incomplete data, which can fail to detect important features or defects. The collected information is very accurate and directly delivers 3D point clouds, which can directly be used to detect useful critical information about a structure, especially on volume-based damage (Chen, 2012).

(2) Sensor movement

Manual sensor positioning on a tripod is labor-intensive, inaccurate, and restricted to safe locations. Hence, it is not reliable for automated data collection. To be able to move a sensor automatically, researchers have used cars (Nishimura et al., 2012), boats (Matsumoto et al., 2012), aerial work platforms (Oh et al., 2008), or railed vehicles (Esser et al., 2000). These systems are not fully automated and are not well suited to cover a complete bridge surface. Still, they reduce workloads and enable data collection up to a speed of 10 km/h.

Remotely piloted or autonomously flying Unmanned Aerial Vehicles (UAVs) are a promising approach to release sensors from static or track-guided positions. Due to technological progress and miniaturization, UAVs are widely available commercially. Some inspection service providers already use UAVs for remote live inspection. Instead of walking around a structure, an inspector directly pilots a UAV equipped with a camera and inspects a structure on screen. The Aerial Robotic Infrastructure Analyst (ARIA) is a cooperation between the Robotics Institute and the Civil Engineering Institute at Carnegie Mellon University lead by S. Singh. Its platform is a commercial UAV equipped with three digital cameras and a 2D laser scanner. Two cameras are grouped to a stereo camera looking straight for navigation purposes and image collection. The third camera is faced upwards to collect images above the UAV, for example at an underpass. The laser scanner enables collection of depth information. The project combines different aspects of UAV, laser scanning and multiple digital cameras, and can collect images and depth information from an arbitrary position.

(3) As-is modelling

As-is Bridge Building Information Modeling (BIM) is the process of generating the digital representation of the "as-is" status of a bridge. The advantages associated with BIM are widely discussed in the literature (Koch et al., 2014; Pătrăucean et al., 2015; Volk et al., 2014). However, BIM models are not broadly utilized in infrastructure asset management, mainly because the current practice for creating an as-is bridge BIM model is a laborious manual task, due to its time-, cost- and knowledge-intensive nature (Tang et al., 2007; Brilakis et al., 2010; Hichri

et al., 2013). Remote surveying techniques, such as laser scanning, have been implemented over the past years for inspection data collection. Instead of spending days or weeks, only a matter of hours are needed to accomplish the laser scanning of a typical highway bridge (Tang et al., 2007). Yet, tens of hours of office work are needed to post-process the point cloud data (PCD) generated from the laser scanner. It is a daunting task, even for a seemingly simple structure. More than two-thirds of human effort required for as-is BIM model creation is dominated by PCD conversion (Brilakis et al., 2010), which may cost thousands of dollars to complete a BIM modelling project.

A few major vendors such as Autodesk, Bentley, Tekla, Graphisoft, and many others provide state-of-the-art BIM commercial solutions. However, these software packages are still far from being fully automated. Wang et al. (Wang et al., 2015) did a review on the current BIM commercial software. Three major bottlenecks in current BIM modelling solutions are summarized in the following paragraph.

First, current 3D modelling or reverse engineering software involves manual conversion through user-guided specification of facility components incorporated with semi-automated 3D primitives fitting. Second, after completing the fitting of CAD entity models to 3D primitives embedded in the PCD, modelers need to manually enrich these 3D geometric primitives with “meaningful” bridge components suitable for manipulation in the BIM environments, as well as define the topological relationships between the bridge components. Finally, existing commercial solutions fail to solve the problem of model interoperability. When passing data between different BIM platforms, the issue of data non-interoperability requires modelers to replicate data input in order to work properly on their own workstation (Fernandes, 2013), giving rise to the possibility of information loss.

According to the core categories of tasks for BIM creation, current research can be grouped into three major parts, namely geometric modelling, object recognition, and relationship modelling. More precisely, geometric modelling aims to generate simplified representation of bridge components by fitting geometric primitives to the PCD, and to acquire the geometric parameters of these primitives. Object recognition aims to label the queried bridge components embedded in the PCD with an object category. Finally, relationship modelling aims to create topological relationships between bridge components.

Although volumetric parametric models are most relevant to BIM, feature extraction approaches that generate the parametric surface-based primitives, especially planar surfaces, are dominant in the literature (Pătrăucean et al., 2015). Widely used segmentation techniques such as KNN (Rabbani et al., 2006), Hough transform (Okorn et al., 2010), RANSAC (Rusu et al., 2009), SVM (Xiong et al., 2013) and so on are leveraged in order to segment the points into classified surfaces. With regard to object recognition, different recognition techniques are studied. Instance-based object recognition approaches recognize objects using prior information of the shape and generic descriptions of objects (Kim et al., 2011). While instance-based object recognition tries to fit objects embedded in PCDs, classes-based recognition approaches aim to match the queried objects against examples from the entire class (Pu & Vosselman, 2009; Zhang et al., 2014a). The contextual knowledge is also used to specify the relationships between objects in the scene, and to yield class labels (Posner et al., 2009; Koppula et al., 2011). In contrast to the aforementioned feature-based data-driven object recognition methods (Volk et al., 2014), model-driven approaches tend to use prior domain knowledge about the context and the objects per se. Dietenbeck et al. (2015) (Dietenbeck et al., 2015) proposed a decision-tree-based expert system which is able to efficiently segment and annotate an object. Belsky et al. (Belsky, M., Sacks, R. and Brilakis, 2013) proposed a rule-processing-based engine for supplementing an IFC file with semantics contained in the building model. Brilakis et al. (Brilakis et al., 2010) outlined a hybrid-based framework by taking laser scanning and video data collected in the field as input. Data fusion methods take advantage of both spatial and visual features, making it more efficient to recognize the object (Zhu & Donia, 2013). Finally, relationship modelling is able to provide additional information to facilitate the object recognition task. Nguyen et al. (Nguyen et al., 2005) proposed an approach that is capable of extracting geometric data from a 3D CAD system and automatically deducing the spatial relations among the building components. Likewise, spatial query language (Nepal et al., 2012; Daum & Borrmann, 2013) is widely studied in literature. However, conventional query-language based methods require deep knowledge of the product model schema (Belsky, M., Sacks, R. and Brilakis, 2013), and they are not flexible enough to be tailored for other domains.

3.2 Damage localization, feature extraction and assessment

(1) Cracks

Abdel-Qader et al. (Abdel-Qader et al., 2003) compared four methods (Sobel edge detector, Canny edge detector, Fast Fourier Transform (FFT), and Fast Haar Transform (FHT)) for extracting cracks in images. The FHT outperformed the other three approaches. Principal Component Analysis (PCA) is a method from multivariate statistics that reduces a large number of variables to a small number by expressing them as linear combinations. For classification purposes, Abdel-Qader et al. (Abdel-Qader et al., 2006) used PCA and calculated the nearest neighbor. Zhang et al. (Zhang et al., 2014b) proposed an image processing chain consisting of noise reduction (smoothing), morphological operators for conditioning (remove outliers, close gaps) and binarization with a threshold. The result was split into small, standard-size patches that were classified using a radial basis function

neural network (RBFNN), Extreme Learning Machine (ELM), Support Vector Machine (SVM), K-nearest Neighbors algorithm (KNN), and a threshold. The best results were achieved with an ELM. Cheng et al. (Cheng et al., 2003) proposed a method to classify cracks with an adaptive threshold. An adaptive threshold overcomes the problem of setting a global fixed threshold. It is calculated based on the mean and standard deviation of image pixel values. Oh et al. (Oh et al., 2008) proposed a method to trace a crack in a grayscale (not binarized) image. Starting from a seed point, it traced a bidirectional crack in the direction of lowest pixel intensity. Orthogonal to this direction, the width was measured using second derivative zero crossings. Adhikari (Adhikari et al., 2014) and Koch et al. (Koch et al., 2014) proposed a similar skeleton-based approach to extract crack dimensions. Morphological operators were used to generate a crack skeleton. Branch points were identified and used to separate a crack into several unbranched sections. Length and width were determined for each section separately. Arena et al. (Arena et al., 2014) presented a way of separating connected micro-cracks in rocks to crack segments by using bisector lines to separate cracks at branching positions. This leads to clean crack segmentation and long crack segments. High fragmentation of cracks is prevented. Adhikari (Adhikari et al., 2014) used half of the perimeter as length assuming that the length of a crack is considerably greater than its width. The ratio between length and area provided the width of a segment. A neural network was trained to estimate crack depth based on crack width.

Table 1. Overview of existing methods for automated bridge inspection

	Data collection		Damage localisation		Damage feature extraction		Damage assessment	Data handling			
	Sensor movement	Surface coverage	Localisation	Classification	Measured unit	Consider damage type		Data storage - comprehensible	Data storage - reproducible	Data modelling	Visualization
Abdel-Qader et al. (Abdel-Qader et al., 2003, 2006)	-	-	**	* Cracks	-	-	-	-	-	-	*
Adhikari et al. (Adhikari et al., 2014, 2013)	-	-	**	** Cracks / Spalling	**	**	*	-	-	-	**
Arena et al. (Arena et al., 2014)	-	-	**	* Cracks	*	**	-	-	-	-	*
Chen et al. (Chen et al., 2012)	-	-	**	* Corrosion	*	*	-	-	-	-	*
Chen et al. (Chen et al., 2011)	**	*	-	-	-	-	-	-	-	-	-
German et al. (now Paal) (German et al., 2012, 2013)	*	*	**	** Cracks / Spalling	-	-	-	-	-	-	*
Guldur, Hajjar (Guldur & Hajjar, 2014)	*	**	***	** Cracks Volumetric damages	**	*	-	-	-	*	-
Koch et al. (Koch et al., 2014)	-	-	***	** Cracks / Spalling	***	**	-	***	*	*	*
Lee et al. (Lee et al., 2008)	**	**	**	* Cracks	-	-	-	**	*	-	-
Li et al. (Li et al., 2014)	*	*	**	* Cracks	**	**	-	*	**	-	**
Matsumoto (Matsumoto, 2013; Matsumoto et al., 2012)	**	**	**	** Cracks / Delamination	**	**	**	-	-	-	**
Mc. Robbie (McRobbie et al., 2011)	*	**	**	* Damages in general	-	-	-	**	*	*	***
Nishimura et al. (Nishimura et al., 2012)	**	**	-	-	-	-	-	*	*	-	-
Oh et al. (Oh et al., 2008)	**	**	**	* Cracks	*	**	-	-	-	-	-
Paal et al. (prev. German) (Paal et al., 2014)	*	*	***	** Cracks / Spalling	-	**	*	-	-	-	**
Pătrăucean et al. (Pătrăucean et al., 2015)	-	-	-	-	-	-	-	-	-	*	-
Tang et al. (Tang et al., 2007)	-	-	-	-	-	-	-	-	-	*	-
Yu et al. (Yu et al., 2007)	-	-	**	* Cracks	**	**	-	-	-	-	**
Zhang et al. (Zhang et al., 2014b)	-	-	**	* Cracks	-	-	-	-	-	-	-
Zhu, Brilakis (Zhu & Brilakis, 2009)	-	-	**	** Air pockets / Discoloration	-	-	-	-	-	-	-
Zhu et al. (Zhu et al., 2011)	-	-	**	* Cracks	***	**	-	*	*	-	*

(- not included / relevant, * basic automation, ** mediocre automation, *** advanced automation)

(2) Corrosion

Rust stains and corrosion can be identified by their specific color. Methods utilizing color information outperform those working on grayscale images only. Son et al. (Son et al., 2014) proposed a method for rust detection, which first transformed the images from RGB (red, green, blue) to HIS (hue, intensity, saturation) color space. A decision tree was identified to be optimal for detecting rust.

(3) Spalling / Scaling

German et al. (German et al., 2012) did work in the area of spalling. Based on four specific characteristics, the size of a spalled region was extracted. The depth of a spalled region cannot be measured, but German et al. used vertical reinforcement to infer spalling severity. To the author's knowledge, there is not much work performed specifically for scaling. Adhikari et al. (Adhikari et al., 2012) infer severity from the difference of intensity of a scaled region to its depth. Further research has to prove if the approach is robust to changes in lighting, scaling type, and other variations. Zhu and Brilakis (Zhu & Brilakis, 2008) presented a method for detecting air pockets. An image pyramid was used in combination with a spot filter to detect round pockets of different size. They were identified by a relatively round decrease in contrast.

(4) Multiple defects

Adhikari et al. (Adhikari et al., 2013) identified cracks and spalling to estimate bridge condition indexing. Paal et al. (Paal et al., 2014) proposed a solution for the related field of post-earthquake index estimation of reinforced concrete columns. To combine the detected damages of spalling and cracks, decision trees were proposed that lead to a structural rating. Different decision trees not only combined detection of multiple damages, but also assessed such damages. However, information necessary to answer node questions cannot be extracted automatically.

3.3 Data handling

Digital records are essential for monitoring long-term bridge performance and maintenance budget planning. CAD (Computer Aided Design) files were used by Oh et al. (Oh et al., 2009) to make crack maps accessible for bridge management systems. Certainly, CAD is intended for a completely different purpose and not designed to store lifecycle data. Damage information cannot be stored in a proper way using this technology.

4. CONCLUSIONS

Manual inspection is a well-established method for assessing the condition of bridges. Different inspections are conducted at different intervals, mainly varying in their frequency, level of detail, and use of additional tools. However, it has been shown that manual bridge inspection is subjective, incomplete, bears safety issues. To overcome these problems, researchers have worked on ways to automate existing inspection schemes. However, there are gaps in knowledge that impede the application of automated bridge inspection. Existing methods are addressing only one damage type, mostly cracks. However, bridge inspection has to identify multiple damage types at the same time. Otherwise, manual inspection still has to be conducted. Furthermore, existing methods are based on sensor data solely and do not consider the structure geometry. Hence, it is only possible to identify a damage type but not its implication. For example, it is possible to identify a crack as such, but it cannot be refined to a structural or non-structural crack. The automated assessment of bridge elements based on extracted damage properties is largely unexplored.

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