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OPTIMISING BRIDGE MAINTENANCE: A CASE STUDY IN ASSESSING BRIDGE CONDITION USING NOVEL TECHNOLOGIES AND METHODS

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Abstract

Bridges are well known as the most critical parts of infrastructures, serving as vital links for transportation networks. However, ensuring their proper functionality, structural safety, and durability requires careful and timely maintenance and regular assessment of their condition. A large infrastructure and a huge number of objects together with economic constraints make this task exceedingly difficult. The traditional bridge maintenance approach is primarily based on periodic visual inspections that can be accompanied by additional destructive or non-destructive tests. Such practice is well-established and accepted among practitioners, but data about bridge conditions, collected through a time-consuming process may pose challenges in interpretation. In the end, it might not provide a comprehensive picture of a bridge's overall health. Therefore, advanced methods are now being used to enhance the overall process. They are based on the usage of new technologies such as unmanned aerial vehicles (drones) equipped with high-resolution cameras, light detection and ranging sensors (Lidar), and other sensors embedded within the structure to obtain more detailed information about bridge condition. This information can then be used together with computational methods like finite element modelling to assess bridge conditions and structural performance on a much higher level. This article presents an approach to assess the condition of an existing case study bridge using state-of-the-art technologies and methods. The condition of the bridge is assessed using a 3d model generated from the photos of the bridge acquired by an unmanned aerial vehicle equipped with a high-resolution camera. Captured bridge geometry is subsequently employed to develop a finite element model, serving as a baseline for vibration-based damage detection analysis.

Keywords: bridge assessment, unmanned aerial vehicle, photogrammetry, operational modal analysis, vibration-based damage detection

1 Introduction

Maintenance schedules mostly rely on reports from regular visual inspections, which remain a common practice among many professionals. However, this approach has well-known limitations [1], prompting extensive research in recent years to enhance current practices. A certain amount of research has been done employing unmanned aerial vehicles (UAV) equipped with high-resolution cameras to remotely perform visual observations. In this way, the need for heavy and expensive equipment for close-distance inspection of hardly reachable bridge parts is potentially removed.

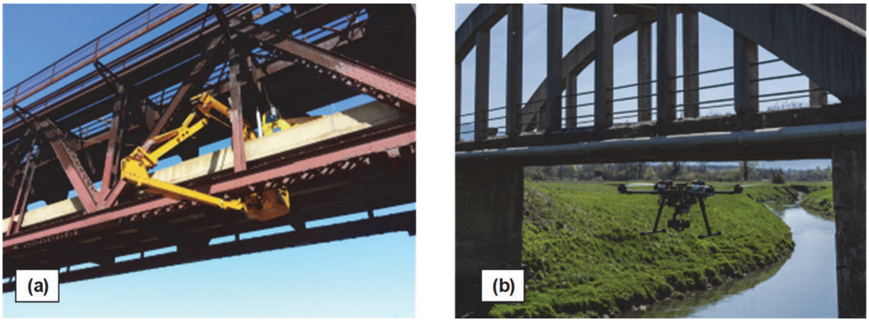

Figure 1 Bridge visual inspections using: a) Under Bridge Inspection Platform ("bucket truck") [2]; b) Unmanned Aerial Vehicles (UAV)

UAV-based bridge inspection can be further extended by coupling close-range photogrammetry with computer vision to extract additional information about the bridge. This includes building geometry [3], presence of construction defects, or other kinds of structural damage (cracking [4], delamination [5], corrosion [6]).

An alternative approach to detect structural damage is based on analyzing changes in bridge vibration characteristics (tracking dynamic parameters) obtained through vibration-based monitoring systems installed on the bridge. To mitigate the application of such techniques from simple lab structures in controlled environments to real-world structures such as existing bridges, more research is needed. When dealing with large structures, especially those exhibiting diverse imperfections and damage caused by age and usage, a major challenge is to precisely capture the condition so it can be used as a reference for validation of developed vibration-based damage detection techniques.

In this article, photogrammetry model was created using photographs taken using UAV equipped with high-resolution cameras. The created model is used for mapping the geometry and defects of the existing case study bridge. Dynamic parameters of the bridge were obtained experimentally using operational modal analysis (OMA) and from the numerical model generated based on field measurements and geometry from a photogrammetry-based 3D model. Experimentally and numerically obtained dynamic parameters were then used as a representation of the damaged and undamaged states of the bridge respectively. Knowing the location, type, and severity from the photogrammetry-based 3D model, vibration-based damage detection using direct mode shape comparison methods [7] was performed and validated.

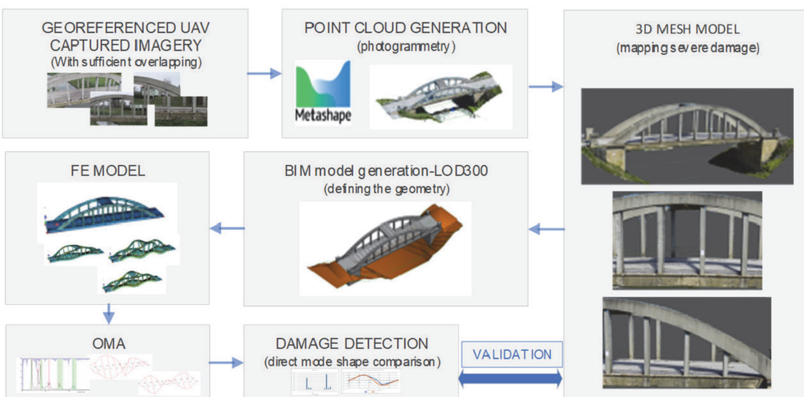

Figure 2 Methodology applied to case study bridge for validation of developed vibration-based damage detection methods

2 Condition of the case study bridge

A case study bridge (Figure 3) is a reinforced concrete tied-arch bridge with the clear span between abutments of 24 m. Bridge passes local road over the Krapina river in Croatia.

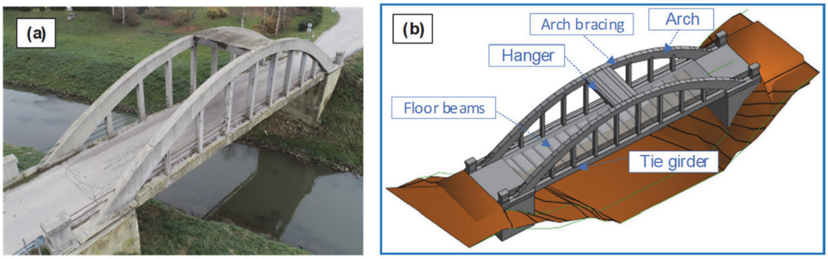

Figure 3 Case study bridge. a) View on the bridge from UAV; b) 3D BIM model of the bridge with marked main structural elements

Aging, usage, and environmental effects caused damage such as cracking, delamination, reinforcement corrosion to some structural elements with varying severity levels. Geometry of the bridge elements was unknown and to precisely map existing damage to the location on corresponding structural element the close-range photogrammetry was used.
UAV inspection of the bridge was carried out using a custom-made quadcopter outfitted with a high-resolution Sony camera mounted on a gimbal for stabilization. The dimensions of the UAV are 1.2m x 1.2m x 0.5m, weights 9.5 kg, with a flight time of approximately 30 minutes. It is equipped with a CubeOrange flight controller running Ardupilot firmware, which is responsible for the low-level attitude control of the vehicle. Additionally, the UAV is equipped with an onboard Intel NUC computer capable of processing sensory data and executing autonomous missions.
Utilizing the acquired georeferenced images captured by the UAV, a point cloud representation of the bridge was generated based on overlapping features in the photographs. Subsequently, this point cloud data was used to develop a 3D mesh model of the bridge, by creating polygons from clusters of adjacent points. High-resolution textures were then applied onto this mesh to produce a detailed model that can be used for the visual detection of structural defects.

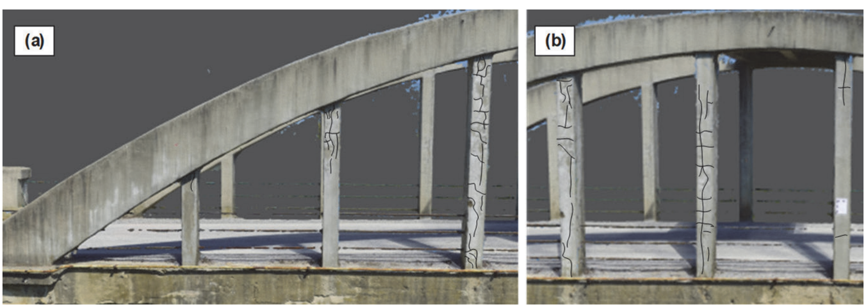

Figure 4 Marked cracks (larger than 0,3 mm) in downstream hangers. (a) side hangers; (b) middle hangers

It may not be feasible to detect some structural defects such as hairline cracks in concrete even from images captured by UAV with high resolution cameras because of unavoidable environmental conditions (shadows, sun reflections, polluted surfaces, etc.). Even if captured on images, such small intensity information may be lost or compromised trough photogrammetry process.

Therefore, the focus was primarily placed on major defects such as delamination and severe cracking observed in field from visual inspection and additionally confirmed by created 3D model. Medium to high severity cracks were detected on most of the RC hangers (Figure 4a, 4b). Cracks severity increased from the side hangers to the ones in the middle of the bridge span where the shortest hangers had the smallest severity. Delamination on concrete cover with rebar corrosion was also present on the floor beams in the midspan (figure 5).
Marked damage at corresponding bridge elements will be used in next section to validate direct mode shape comparison methods for damage detection. The second axiom of SHM [8] states that damage assessment requires comparison between two system states, thus in the following sections, mode shapes obtained for undamaged and damaged state will be compared. Mode shapes obtained from FE model will represent undamaged state while the experimentally measured represent damaged state.

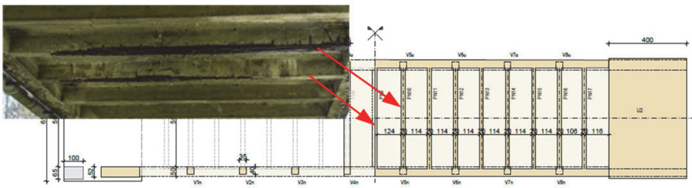

Figure 5 Delamination of concrete cover at midspan floor beams

2.1 Operational modal analysis

Dynamic parameters such as damping, natural frequencies and mode shapes of the bridge were measured on-site using operational modal analysis (OMA), also known as output only modal analysis [9]. These parameters were extracted from a 64-seconds vertical acceleration time series at 20 locations along bridge deck (Figure 6.(a)), resulting in a modal model with 20 degrees of freedom (DOFs). A multi-setup sensor position was used due to the limited number of accelerometers. High sensitivity piezoelectric accelerometers (sensitivity of 1000 mV/g) were utilised along with the Bruel & Kjaer 3560C analyser and computer program PULSE LAB SHOP for data acquisition. For modal identification, frequency domain decomposition method [9] was employed and first three torsional mode shapes with associated natural frequencies were estimated (figure 6b.).

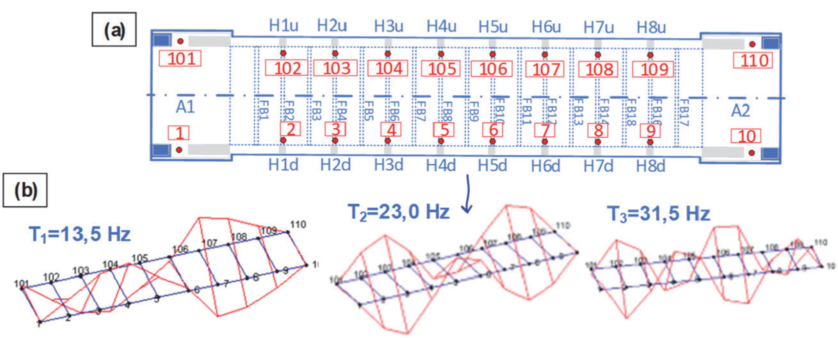

Figure 6 Operational modal analysis. (a) Location of measurement points; (b) Estimated natural frequencies and mode shapes for damage state

3 Finite element model

To calculate mode shapes for undamaged state, numerical finite element model was developed using commercial software "SoFiSTiK" [10] specialised for practical structural analysis tasks. Bridge deck and arch are modelled as area finite elements while hangers, floor beams, tie girder and arch bracing as beam elements taking into the account eccentricities between elements. Modulus of elasticity for all concrete members was taken with value of 33 000 MPa and concrete density of 25 000 kg/m^3. Bridge is fully connected with the abutments, so fixed boundary conditions was used at each end. Mode shapes (Figure 7.) and natural frequencies were calculated using Lanczos method [11]. The primary load case, defined as a combination of permanent loads (self-weight of the structure and additional weight), was used to establish the initial state for the modal analysis. In this way, the contribution of deflection and forces from permanent loads are considered.

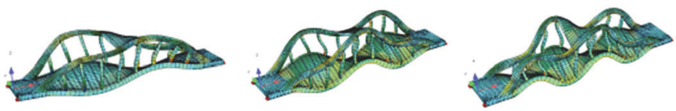

Figure 7 Torsional mode shapes from numerical model for undamaged state.

Estimated mode shapes from FEM contain complete set of DOFs while the experimentally measured contain only DOFs associated with the limited number of measured points in selected directions. Moreover, OMA may not reliably estimate as many mode shapes as numerically calculated. Therefore, a model reduction process is necessary to equalise the number of DOFs. This process involved matching the geometrical positions of each measured point to the node in numerical model with the closest coordinate position.

4 Vibration-based damage detection

The fundamental premise for vibration-based damage detection (VBDD) methods is that damage or any change in the structural system will affect the stiffness consequently influencing vibration characteristics described by dynamic parameters.
In the following text, VBDD methods based on direct mode shape comparison are presented. Those methods assume high sensitivity of mode shapes on presence of damage; therefore, damage could be detected from the change in mode shapes. Mode shape variance can be quantified by different indexes, such as Modal Assurance Criterion (MAC), Coordinate Modal Assurance Criterion (COMAC) and Enhanced Coordinate Modal Assurance Criterion (ECOMAC) [12]. The MAC factor, ranging between 0 and 1, compares two mode shapes with 1 indicating perfect similarity. COMAC and ECOMAC assess differences between two sets of mode shapes (undamaged and damaged states), providing values for each degree of freedom. A low COMAC value suggests potential damage location, while a low value of ECOMAC indicates very high corelation of mode shapes, so damage location is indicated by high ECOMAC value.
From the results presented in Figure 8. all methods managed to detect significant difference between undamaged state (mode shapes from FE model) and damaged state (mode shaped estimated with OMA). This can be seen from the Figure 8a. For first torsional mode shape T1 the highest difference between mode shapes is obtained. For damage localisation COMAC and ECOMAC factors have been used. Highest value of ECOMAC is obtained at station 13,5 m (midspan of the bridge, Figure 8c) which correlates with delamination described on Figure 5. Relatively low values (below 0,6) of COMAC factor (Figure 8b) were obtained at each station of observed point (at connection of hangars with tie girder). This may indicate concrete cracking of hangers (visual inspection in field and on 3D model proved medium to large cracking in each hanger).

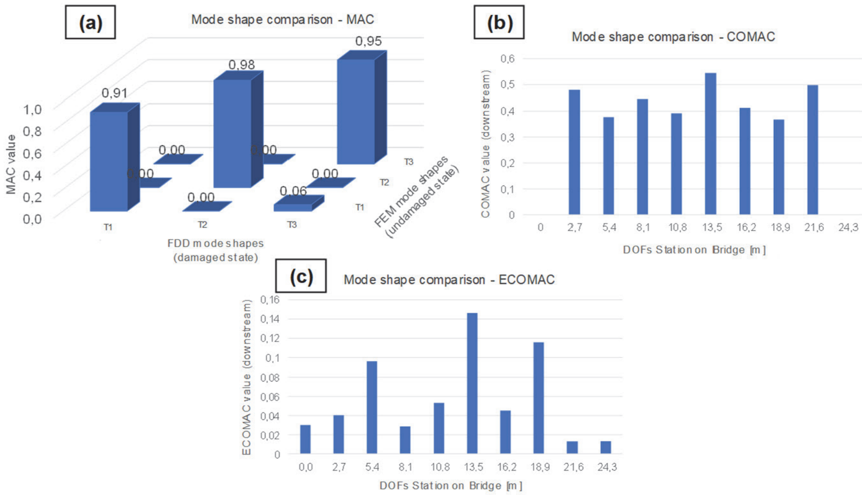

Figure 8 Results of mode shape comparison for damage detection. (a) MAC values; (b) COMAC values; (c) ECOMAC values

5 Discussion and conclusion

The methodology presented in this article involves developing a digital bridge model using UAV captured images and photogrammetry. This model can be used to document bridge visual defects and its geometry, thereby further enhancing the quality and objectivity of visual inspections. It also facilitates transition from in-filed damage detection to the digital environment.

Such digital models, as it is presented in this article, can be used for assessing the damage identification capabilities of developed VBDD techniques on existing bridges, with multiple damage locations and in real conditions. Used VBDD methods were based on direct mode shape comparison. The damaged condition was presented with several torsional mode shapes obtained from the measurements with known damage locations including cracked hangers and delamination of floor beams at midspan. Undamaged states were presented with equivalent mode shapes obtained from the FEM model. Used factors such as MAC, COMAC and ECOMAC successfully detected differences between selected mode shapes marking the existence and possible location of damage.

The major drawback of presented approach is that the FEM model is prone to modelling simplifications, therefore presented differences in mode shapes consist of errors that may not be damage correlated, resulting in false-positive outcomes of damage detection. Therefore, for further research, it is recommended to extend this approach with the FEM updating process, to the minimize difference between FEM and real structure and in that way increase the reliability of damage detection.

Additionally, from the authors' experience from the case study, improvements are still needed primarily in the image acquisition process. Detailed information about the bottom side of the bridge deck is often crucial for assessing the bridge's condition. Challenges arise in capturing images of the bottom side of the bridge deck due to the signal loss which reduces UAV manoeuvrability. Autonomous flight with predefined trajectory offers huge potential to overcome these challenges.

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