Towards Detailed Digital Examination of Masonry Railway Bridges Using Terrestrial Laser Scanner

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Abstract:
Masonry railway bridges make up a significant number of the UK railway network. These bridges require regular condition assessments by transportation authorities to identify and evaluate defects that can result in structural failures. Common defects in such masonry structures are spalling, crack, bulging, joint defects and loss of section. The conventional bridge examination process is highly dependent on visual inspection, that is, an inspector should be on site and, as a result, such inspection can cause health and safety concerns as well as traffic interruption for a significant period. Digital examination process can replace the visual examination and it can subsequently reduce the number of site visits, traffic interruptions, and health and safety concerns. It can eventually speed up the examination process and improve the efficiency of inspectors' work. Terrestrial laser scanner (TLS) can be used to identify defects and analyse their severity on the surface of bridge structures. The point cloud dataset captured by TLS can be analysed using commercially available software packages to identify defects and assess their severity. However, a review of the literature reveals that despite the importance of masonry railway bridges, there is scarce literature focused on exploring and comparing different software solutions for the purpose of defect detection and analysis in such bridges. Therefore, this exploratory research aims to demonstrate the applicability of digital examination for masonry railway bridges through the application of TLS. This paper contributes to knowledge by establishing a practical basis to identify defects in masonry railway bridges using commercially available software tools.

Keywords:
Digital Examination, Masonry Bridge Defects, Point Cloud Data Analysis, Defect Detection.

1 Introduction

The U.K.'s transport network contains a large number of masonry bridges, and these bridges are highly durable and require moderate maintenance because of their arch constructions (Wiggins, 2018). Around 47% of the railway bridge asset in the UK are masonry structures (Orbán, 2004) and in Europe, it is around 60% of total railway bridges (Jing et al., 2022). Although these bridges do not require much maintenance, a periodical inspection is necessary to ensure that the bridges are in operable condition. Current bridge inspection procedures are highly relying on a physical visit to the site of a bridge and manually inspecting the condition of the bridge by an expert engineer. It is not only time-consuming but also triggers other issues such as traffic interruption, the closure of a road or a lane, risk of working overhead or underneath a bridge (Talebi et al., 2022). Also, the process requires significant planning, pre-visit to the sites carrying out safety equipment and staff travelling to the site. The digital examination can facilitate bridge condition monitoring more quickly and cost-effectively than the traditional physical inspection processes with a significant reduction in traffic closure and risk of working at height and under-bridge inspections. A study on four US bridges by Wells and Lovelace (2017) shows that digital examination using Unmanned Aircraft System (UAS) can be successfully performed in full compliance with National Bridge Inspection Standard (NBS). Instead of physical inspection, capturing digital information of an asset and analyzing that later is the key aspect of digital examination. A range of techniques could be used to capture digital data such as Terrestrial Laser Scanning (TLS), 360-degree imaging devices, Close Range Photogrammetry (CRP), Infrared thermography (IR) and Ground Penetrating Radar (GPR) (Abu Dabous and Feroz, 2020). Terrestrial laser scanning (TLS), also referred to as terrestrial LiDAR (light detection and ranging), acquires XYZ coordinates of numerous points by emitting laser pulses toward these points and measuring the distance from the device to the target. Popular laser scanners in the market include FARO, Leica, Surphaser, Topcon and Trimble. Bespoke software packages (e.g. SCENE software for FARO laser scanners) are generally required for managing and analysing the data because of the large amount of data stored in a TLS point cloud. 360 imaging cameras are designed to capture high-resolution spherical immersive images for efficient visual documentation of an environment. 360 imaging cameras are usually lightweight and easy to transport and deploy. Individual 360 images can be linked together to create a virtual tour (similar to Google Street View) to enable users to move between captured positions. 360 imaging cameras can be mounted on a standard tripod, vehicles or under a UAV for aerial data capture (Rausch et al., 2022). For example, iSTAR FUSION 360 Degree Rapid Imaging Panoramic Camera is a 360 camera that can be mounted on a tripod. It has 4 pre-calibrated sensors delivering a full spherical image. GPR generates a subsurface image using electromagnetic energy, and an infrared camera produces images based on the reflected infrared radiation from an object. Unmanned aerial vehicles (UAVs) are a class of aircraft that can fly without the onboard presence of pilots. Unmanned aircraft systems consist of the aircraft component, sensor payloads and a ground control station. When it is remotely controlled from the ground, it is called RPV (Remotely Piloted Vehicle) and requires reliable wireless communication for control. UAVs are classified based on altitude range, endurance and weight. It can support a wide range of applications including examination of the top of bridges, aerial photography, geographic mapping, and disaster management. The smallest categories of UAVs are often accompanied by ground-control stations consisting of laptop computers or mobile devices as well as other components that are small enough to be carried easily with the aircraft in small vehicles. In recent years, increasing research efforts and developments are improving UAV for various applications and reliability. Also, a shortage of skilled onsite crew members is a bigger problem. It is widely accepted that a minimum of three staff members is required to operate a UAV (Elghaish et al., 2021). Each instrument has its advantages and drawback. For example, infrared thermography can quickly produce thermal distribution in a structural element; however, the negative impacts of absorption of thermal energy within daytime should be mitigated by capturing thermal images within certain hours of a day (normally 2 hours after the sunset); 360-degree images can provide information about the surface condition; however, this technique is not suitable for subsurface defects and so on. A significant amount of research work is done in the field of construction and building engineering for the detection of bridge defects from high-resolution visual images and point cloud data; however, many of those do not consider masonry bridges due to their complex surface texture. Therefore, this paper aims to demonstrate the feasibility of digital examination for masonry railway bridges using TLS. The research reported in this paper attempts to answer to the following question: how the analysis of 360 images and point cloud data can be used to identify defects and quantify their severity respectively in masonry railway bridges?

2 Literature Review

Masonry defects in built structures are generally categorised as bulging and leaning of walls, failure in bonding and defects in joints, development of cracks, corrosion on the surfaces and defective cavity walls (Noy and Douglas, 2005). Cavity walls are not part of bridge structures rather it is found in buildings. Considering reference documents of the Network Rail in the UK, the masonry bridge defects can be classified as i) bulging, ii) crack/fracture/ring separation, iii) spalling, iv) joint defect and v) loss of section (Network Rail L3 / CIV / 006 Part 1E, 2019). The same document outlines the way to further classify these defect categories into several severity levels based on the dimension and location of the defects. Therefore, it is necessary to understand the specific measurement requirements for each defect for the development of an effective digital examination framework for masonry bridges. Table 1 shows the defect types and their corresponding measurement requirements for detailed examination of a typical masonry bridge.

Table 1. Defect types and measurement requirements for detailed examination. (Source: Network Rail L3/CIV/006 Part 1E, 2019, pages 23-30)

Measurement requirements	Defect type				
	Bulging	Crack/Fracture	Spalling	Joint defect	Loss of section
Length	Yes	Yes	Yes	No	Yes
Width	Yes	No	Yes	No	Yes
Depth	No	No	Yes	Yes	No
Area	Yes	Yes	Yes	Yes	Yes
Distortion angle	Yes	No	No	No	No

It is found in Table 1 that there are three basic types of measurement required to complete the detailed inspection process. These are:

i) Area measurement for the estimation of surface area covered by a particular defect.

ii) Linear measurement for the quantification of length, width, and depth of a particular defect.

iii) Angular measurement for the magnitude of distortion angle.

There is a significant application of digital technologies found in the literature concerning bridge inspection. Peng et al. (2020) and Wang et al. (2020) demonstrated the use of high-resolution 2D images captured using an Unmanned Aerial Vehicle (UAV) to monitor cracks in concrete structures. Rau et al. (2017) developed a graphical user interface-based system to detect cracks and spalling on concrete bridges from a high-resolution image. Yan et al. (2021) demonstrated the use of visual images (RGB) and lidar data captured using UAV to generate a point cloud model of the bridge and quantify cracks on concrete structures (Talebi et al., 2021). Tian et al. (2021) propose a method for measuring force in cable bridges using UAV-captured data and computer vision algorithms which shows good agreement with the traditional measuring methods. Rhee, Choi et al. (2019) conducted research to show the condition of concrete bridges by analysing GPR-captured data to detect water penetration. Kushwaha et al. (2018) used TLS and CRP to generate point cloud data and analyse deck linearity deformation and deck thickness measurement in different bridges. In an extended study, the authors used GPR to generate subsurface profiles for the detection of water penetration, crack voids and rebar y conducting subsurface profile analysis (Kushwaha et al., 2020). Ayele et al. (2020) used UAV-driven photogrammetry to construct 3D models which were analysed to identify cracks and to measure the width and length of the cracks. Kim et al. (2018) used photogrammetry to construct 3D models which are collected using a UAV drone. In a comprehensive review of the application of laser scanning technology in the civil engineering and building engineering domain, Rashidi et al. (2020) have shown that TLS technology and point cloud data analysis has been successfully implemented for condition monitoring of structural assets throughout the globe. UAV has two major applications namely 3D model construction and automatic damage detection with some limitations such as significant data processing time with the need for high-power computing, the requirement of skilled and trained persons etc. (Ayele et al., 2020). However, with the rapid development of cloud computing technologies high computing power and big data processing are no longer significant challenges.

3 Methodology of Digital Bridge Examination

The proposed digital bridge examination process involves three steps namely data capture, data processing and data analysis as presented in Figure 1.

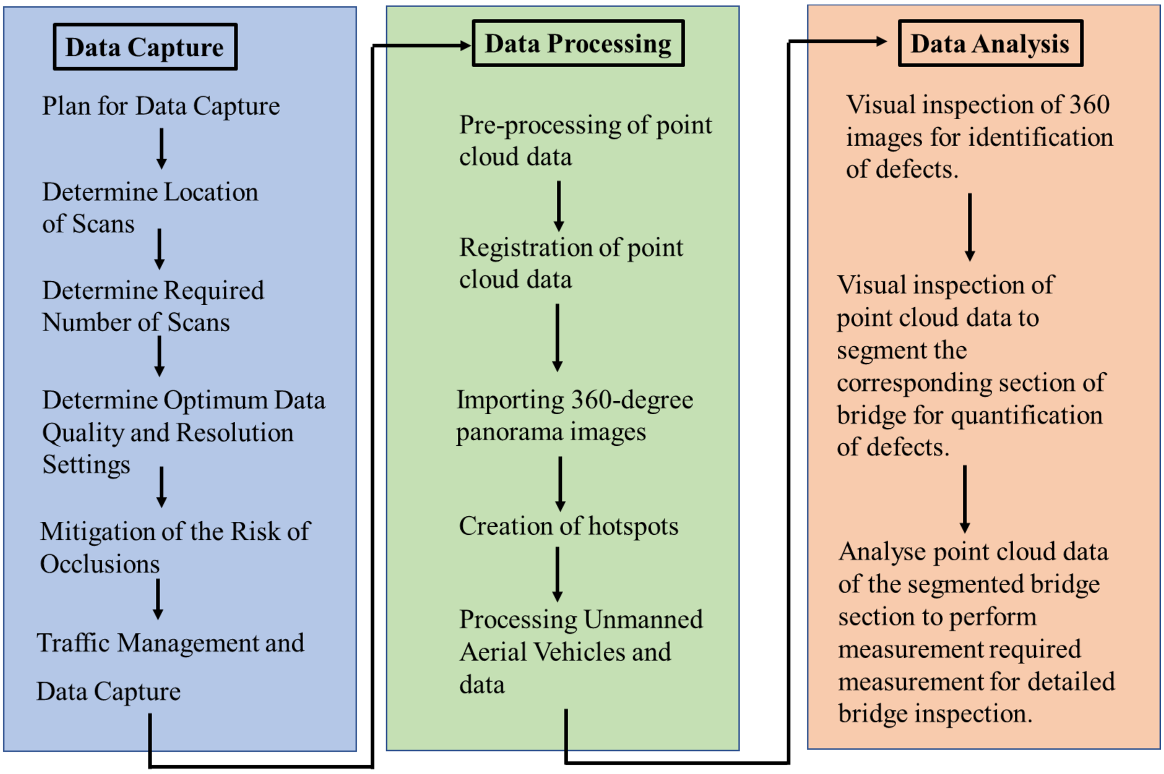


Figure 1. The proposed digital bridge examination process

The data capture activities start with proper planning for data capture which includes the determination of scan locations, determination of the number of scans required, optimum data quality and resolution setting, mitigation of risk of error, traffic management and data capture. The basic parameters of quality and resolution need to be correctly selected to obtain an accurate as-built data set. Having higher resolution and quality can increase the accuracy of data sets but they also significantly increase the time required to capture data. It is recommended to have more scans at lower scanner settings, rather than having a lower number of scans with higher settings. There are limitations which can have an impact on the workflow and the quality of the final data set. The most frequent instances are vegetation, vehicles and pedestrians obscuring capture, poor light, flooding, damp/rain, litter, animals, difficult terrain, limited safe working space, parking restrictions, narrow footpaths, existing structures and compass error. Vegetation and obstructions are common problems at many sites, obscuring data and preventing access in some cases. At structures where vegetation is an observation constraint occluding part of a structure from view, scans are taken in varying locations to capture as much of each structure as possible. Occlusion in data from obstructions is mitigated as much as possible by scanning in varying locations to capture as much of each structure as possible. A compass error occurs when the TLS detects a strong magnetic field, indicating the compass direction would not be accurate in a scan at that location. Strong magnetic fields can be caused by a variety of electromagnetic devices such as telegraph lines and large motors. Moving the TLS away from the suspected source of the magnetic interference or alternatively, turning compass data off to allow a scan to be completed (FARO, 2019) can resolve the error.

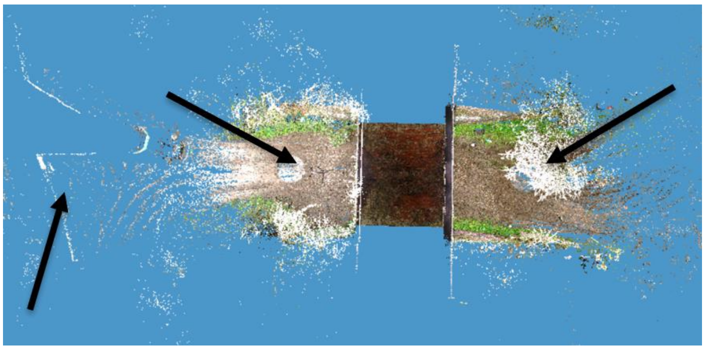


Figure 2. Example of noises in a point cloud dataset.

The data processing step includes cleaning and registration of point cloud data, importing 360 panorama images and creating a hotspot, and processing UAV data. Generally, raw data points acquired by TLS contain noise, which affects the registration and later the data analysis. The noise can be reduced using filters or manually. Data cleaning is a vital step to accelerate the point cloud registration workflow. In Figure 2, an example of noise in the point cloud dataset has been given. Point cloud processing software tools mostly have different filtering functions; however, the accuracy level is not often great. Hence, manual effort is required to clean the point cloud data. The registration process could be either target based or targetless. In target-based registration, pre-processing may be used to identify targets automatically (Sabbaghzadeh et al., 2022). For this purpose, artificial targets, spheres, checkerboards or circular flat targets can be used. The current project uses sphere and checkerboard targets as they may also be fitted automatically using automatic object detection, whereas circular flat targets can only be fitted manually with the object marker or from a selection of scan points (Da Rocha et al., 2018). The panoramic images captured by the TLS/360-degree camera can be used to display the defects found during the digital examination of the structure, and their exact location on the structure (Elghaish et al., 2020). Compared to a regular visual examination report, the virtual environment interface offers an interactive and easy-to-understand format. “3D Vista” is a tool that has been used to create an interactive panoramic virtual environment in the current project. The UAV capture RGB data can be processed in the following steps: a) Align and match points in Nadir images, followed by adding Ground Control Points (GCPs) and referencing them; b) Align and match points in Oblique 1 images, followed by adding GCPs and referencing them; c) Align and match points in Oblique 2 images, followed by adding GCP’s and referencing them; d) Merge the Nadir and Oblique images; e) Create Point Cloud; f) Create 3D model, and g) Create Orthomosaic.

4 Implementation of the proposed method

The proposed methodology for the digital inspection of masonry bridges is implemented on six different railway bridges in England. TLS-captured point cloud data, 360 images and UAV-captured point cloud data are collected for analysis to detect and quantify the defects mentioned in Table 1. Point cloud data is captured with a resolution of 10240 × 4267 pixels and point distance of 6.136 mm/10 m. 360 images are captured with resolution of 2748 × 3664 pixels. FARO Focus 3D (X330) TLS scanner was used for point cloud data capture and ISTAR 360 panoramic camera was used for 360 image capture. The registration process of TLS captured point cloud data is accomplished using FARO SCENE software. Figure 3 shows the cleaned and registered point cloud data of one of the bridges used in the project.

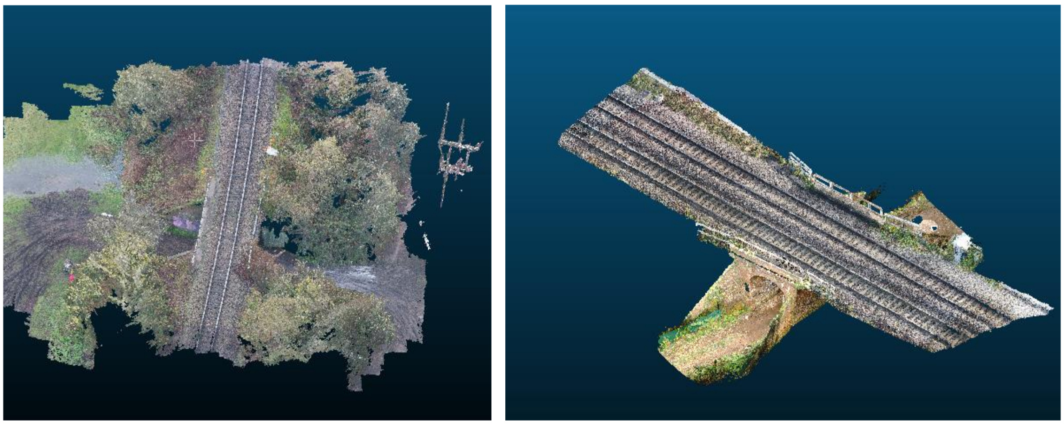
Figure 3. Cleaned and registered point cloud data of a masonry bridge.

Figure 4-a shows the flat representation of 360 images of the same bridge shown in Figure 2. Figure 4-b shows the folded representation of the 360 images shown in Figure 3-a in a virtual tour environment.

(a) (b)

Figure 4. (a) Example of a captured 360 image (flat image), (b) Example of a 360 virtual tour (folded image)

Figure 5-a shows the UAV-captured processed point cloud data from another bridge from the top side of the track and Figure 5-b shows the combined TLS and UAV point cloud data of the same bridge after data cleaning and registration. The point cloud data and the 360 images are used for the inspection of bridges. The detection of defects has been performed by examining the visual image, and the corresponding point cloud data has been used for quantification of defects. An open-source software called CloudCompare is used to perform the analysis of point cloud data for this project as CloudCompare software has demonstrated the capability of efficiently analysing point cloud data and it has been widely used in several research endeavours in this field (Girardeau-montaut, 2016).



(a) (b)

Figure 5. (a) captured data by UAV from the topside of a track, (b) image of combined UAV and TLS captured point cloud data.

Figure 6 shows examples of crack detection and joint defect detection from 360 image and point cloud data. On the top left of Figure 6, window 'A' shows the presence of a crack and window 'B' shows the presence of joint defects. On the bottom right image, point cloud data of the corresponding bridge section is shown with crack and joints defects highlighted. The scalar field representation of the analysis result at the right of the image and it shows the corresponding areas of crack and joint defect in a clearer way.

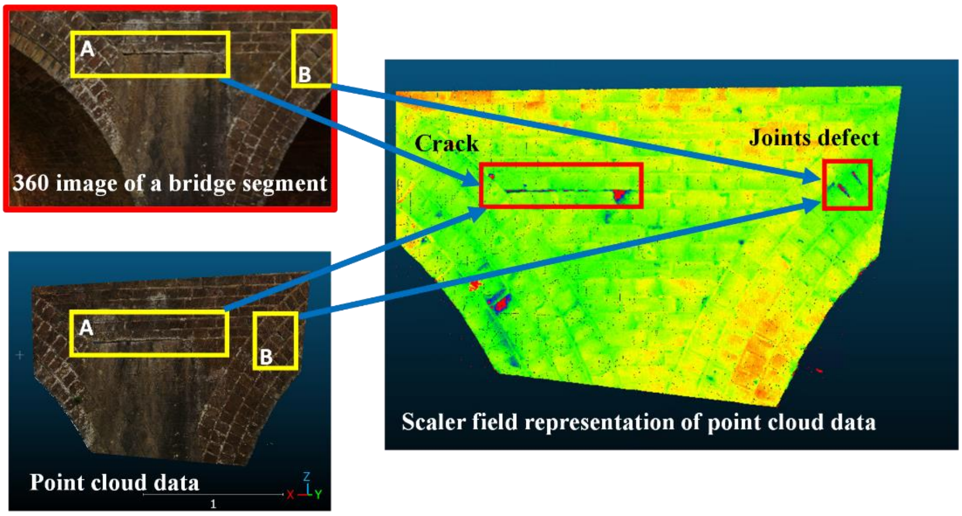
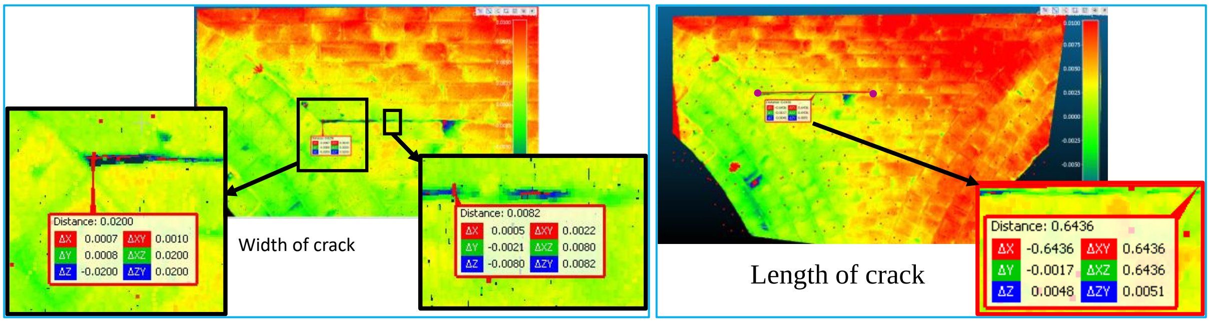


Figure 6. Detection of crack and joint defect.

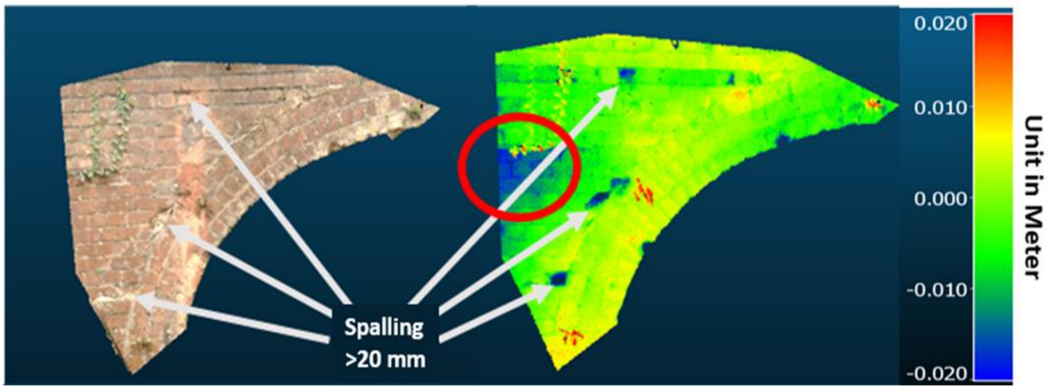
Figure 7-a and Figure 7-b show examples of measuring the width of the crack and the length of the crack from point cloud dataset. CloudCompare software allows users to estimate the distance between any two picked points from a point cloud (Girardeau-Montaut, 2015). Using that tool, the linear distance between two selected points can be measured and which facilitates the length and width of the crack as shown in Figure 7. This tool can be used to measure the linear distances required according to Table 1. Detection of spalling can be achieved from visual inspection of 360 images; however, the quantification requires some additional analysis to be performed using point cloud data. The technique implemented for the analysis is to create a reference surface that represents a healthy state of the masonry structure and then estimates the deviation of point could data from the reference surface. Bulging and loss of section can be quantified similarly.



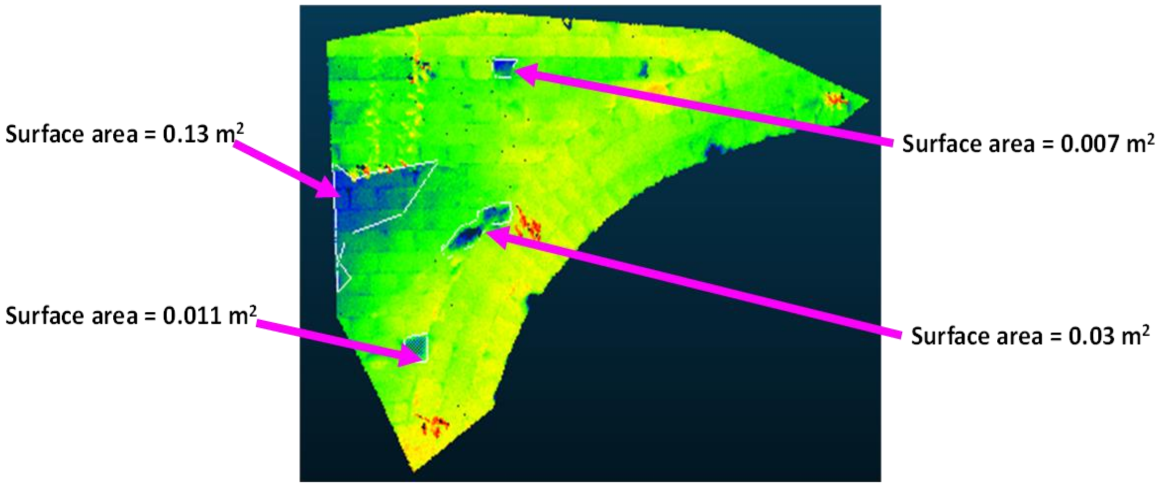
(a) (b)

Figure 7. (a) measurement of the width of the crack, (b) measurement of the length of the crack.

Figure 8-a shows an example of spalling detection using the proposed method at less than 20 mm depth and Figure 8-b shows the quantification of spalling in accordance with the measurement requirements presented in Table 1. The linear measurement related to the depth of spalling can be achieved from the colour bar associated with the scaler filed representations in Figure 8-a. Measurement of any area can be performed in CloudCompare by bounding that area with a polyline and extracting the estimated area from its property pane. Figure 8-b shows an example of area measurement for spalling.



(a)



(b)

Figure 8. (a) detection of spalling from point cloud data, (b) quantification of spalling.

5 Conclusion and Further Research

Adopting digital inspection for monitoring masonry bridges would enhance the safety and quality of the inspection process, and it would reduce the time required and cost associated with the inspection process for large multi-spanned bridges (Talebi et al., 2022). Point cloud data and 360 images obtained from TLS scanning would facilitate the shift toward digitalisation of the masonry bridge inspection process. Literature shows that significant research has been conducted in this domain; however, these are mostly concentrated on concrete structures, or those studies are limited to the laboratory environment. In this paper, a methodology for the digital inspection of masonry bridges is presented and the proposed methodology is implemented in the field (five different railway bridges). The results established the feasibility of implementing this method considering 360 image and point cloud data analysis for masonry defect detection and measurement respectively. It also shows the practicability of using point cloud data and 360 images to digitalise the masonry bridge inspection process. Detection and measurement for all the defects presented in Table 1 are not demonstrated in the current paper due to the absence of some defects in the available data set. However, it is expected that the proposed method can be successfully implemented for all detection and quantification of all defects as these would be the extension of similar processes. The current research considers using CloudCompare software only; hence, future research will focus on the ability of other popular point cloud software to perform similar analysis.

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7 References

Abu Dabous, S. and Feroz, S. (2020) ‘Condition monitoring of bridges with non-contact testing technologies’, Automation in Construction, 116(October 2019). doi:10.1016/j.autcon.2020.103224.

Ayele, Y.Z. et al. (2020) ‘Automatic crack segmentation for uav-assisted bridge inspection’, Energies, 13(23), pp. 1–16. doi:10.3390/en13236250.

Da Rocha C, Tezel A, Talebi S, et al. (2018) Product modularity, tolerance management, and visual management: Potential synergies. In the 26th Annual Conference of the International Group for Lean Construction. Chennai, India: IGLC, 18-20.

Elghaish F, Hosseini MR, Talebi S, et al. (2020) Factors driving success of cost management practices in integrated project delivery (IPD). Sustainability 12(22).

Elghaish F, Talebi S, Abdellatef E, et al. (2021) Developing a new deep learning CNN model to detect and classify highway cracks. Journal of Engineering, Design and Technology. DOI: 10.1108/JEDT-04-2021-0192.

FARO (2019) Error-Code 1830 Compass Failure with the Focus Laser Scanner. Available at: https://knowledge.faro.com/Hardware/3D_Scanners/Focus/Error-Code_1830_Compass_Failure_with_the_Focus_Laser_Scanner (Accessed: 9 September 2022).

Girardeau-montaut, D. (2016) ‘CloudCompare’, in France: EDF R&D Telecom ParisTech, 11. Available at: http://pcp2019.ifp.uni-stuttgart.de/presentations/04-CloudCompare_PCP_2019_public.pdf (Accessed: 30 June 2022).

Girardeau-Montaut, D. (2015) CloudCompare version 2.6.1. user manual. Available at: http://www.danielgm.net/cc/ (Accessed: 7 March 2022).

Jing, Y., Sheil, B. and Acikgoz, S. (2022) ‘Segmentation of large-scale masonry arch bridge point clouds with a synthetic simulator and the BridgeNet neural network’, Automation in Construction, 142(April), p. 104459. doi:10.1016/j.autcon.2022.104459.

Kim, I.H. et al. (2018) ‘Application of crack identification techniques for an aging concrete bridge inspection using an unmanned aerial vehicle’, Sensors (Switzerland). doi:10.3390/s18061881.

Kushwaha, S.K.P. et al. (2020) ‘Analysis and Integration of Surface and Subsurface Information of Different Bridges’, Journal of the Indian Society of Remote Sensing, 48(2), pp. 315–331. doi:10.1007/s12524-019-01087-2.

Kushwaha, S.K.P., Pande, H. and Raghavendra, S. (2018) ‘DIGITAL DOCUMENTATION, BRIDGE DECK LINEARITY DEFORMATION AND DECK THICKNESS MEASUREMENT USING TERRESTRIAL LASER SCANNER (TLS) AND CLOSE RANGE PHOTOGRAMMETRY (CRP)’, ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, IV–5(5), pp. 47–51. doi:10.5194/isprs-annals-IV-5-47-2018.

Network Rail L3 / CIV / 006 Part 1E (2019) ‘NR / L3 / CIV / 006 Part 1E Structures Defects’.

Noy, E.A. and Douglas, J. (2005) Building Surveys and Reports. 3rd edn. Edited by M. Malden. Oxford: Blackwell Publication.

Orbán, Z. (2004) ‘Assessment, reliability and maintenance of masonry arch railway bridges in Europe’, Proceedings of 4th International Conference on Arch Bridges, Barcelona, (152–161), pp. 1–10. Available at: https://caminstech.upc.edu/sites/default/files/Assessment,%20Reliability%20and%20Maintenance%20of%20Masonry%20Arch%20Railway%20Bridges%20in%20Europe.pdf. (Accessed: 26 October 2022).

Peng, X. et al. (2020) ‘The Feasibility Assessment Study of Bridge Crack Width Recognition in Images Based on Special Inspection UAV’, Advances in Civil Engineering. Edited by X. Fan, 2020, pp. 1–17. doi:10.1155/2020/8811649.

Rashidi, M. et al. (2020) ‘A decade of modern bridge monitoring using terrestrial laser scanning: Review and future directions’, Remote Sensing, 12(22), pp. 1–34. doi:10.3390/rs12223796.

Rau, J.Y. et al. (2017) ‘Bridge crack detection using multi-rotary UAV and object-base image analysis’, International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives, 42(2W6), pp. 311–318. doi:10.5194/isprs-archives-XLII-2-W6-311-2017.

Rausch C, Talebi S, Poshdar M, et al. (2022) Tolerance management domain model for semantic enrichment of BIMs. Automation in Construction 141: 104394

Rhee, J.Y., Choi, J.J. and Kee, S.H. (2019) ‘Evaluation of the Depth of Deteriorations in Concrete Bridge Decks with Asphalt Overlays Using Air-Coupled GPR: A Case Study from a Pilot Bridge on Korean Expressway’, International Journal of Concrete Structures and Materials. doi:10.1186/s40069-018-0327-7.

Sabbaghzadeh M, Sheikhkhoshkar M, Talebi S, et al. (2022) A BIM-based solution for the optimisation of fire safety measures in the building design. Sustainability 14(3): 1626.

Talebi S, Koskela L and Tzortzopoulos P (2018) Tolerance compliance measurement using terrestrial laser scanner. 26th Annual Conference of the International Group for Lean Construction: Evolving Lean Construction–Towards Mature Production Across Cultures and Frontiers, Chennai, India.

Talebi S, Koskela L, Tzortzopoulos P, et al. (2021) Causes of defects associated with tolerances in construction: A case study. Journal of Management in Engineering. DOI: 10.1061/(ASCE)ME.1943-5479.0000914.

Talebi S, Wu S, Al-Adhami M, et al. (2022) The development of a digitally enhanced visual inspection framework for masonry bridges in the UK. Construction Innovation: Information, Process, Management. DOI: 10.1108/CI-10-2021-0201.

Tian, Y. et al. (2021) ‘Noncontact cable force estimation with unmanned aerial vehicle and computer vision’, Computer-Aided Civil and Infrastructure Engineering, 36(1), pp. 73–88. doi:10.1111/mice.12567.

Wang, H.F. et al. (2020) ‘Measurement for cracks at the bottom of bridges based on tethered creeping unmanned aerial vehicle’, Automation in Construction, 119(February 2019), p. 103330. doi:10.1016/j.autcon.2020.103330.

Wells, J. and Lovelace, B. (2017) Unmanned Aircraft System Bridge Inspection Demonstration Project Phase II Final Report (No. MN/RC 2017-18). Available at: https://rosap.ntl.bts.gov/view/dot/32636.

Wiggins, D. (2018) Masonry Bridges and the Importance of Lime, The Building Conservation Directory. Available at: https://www.buildingconservation.com/articles/masonry-bridges/masonry-bridges.htm (Accessed: 9 September 2022).

Yan, Y. et al. (2021) ‘Towards automated detection and quantification of concrete cracks using integrated images and lidar data from unmanned aerial vehicles’, Structural Control and Health Monitoring. doi:10.1002/stc.2757.