# Recent developments and ongoing challenges in the implementation of UAS assisted bridge inspections

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ABSTRACT: In the past decade, the use of drones, or unmanned aircraft systems (UAS), to supplement engineering activities such as structural inspections has increased considerably due to the advances in the associated technology in terms of UAS positioning, operation, control, and payload capacity. High-resolution imagery of structures obtained using drones fitted with digital cameras can be post-processed using computer vision and photogrammetry techniques to potentially provide more reliable structure geometry and inventory, structure condition, and structural performance (SHM) data, in less time and possibly at a lower cost than current methods. This approach can aid Principal Inspections for bridge structures, particularly where access is difficult, obviating the need for expensive under-bridge equipment and/or lane closures. However, challenges remain for the widespread implementation of drones for bridge inspections, primarily relating to measurement accuracy and stabilisation of images recorded during drone flight, while issues around safety and regulation can also limit UAS operation for this purpose. This paper presents a brief overview of these challenges and investigates the use of computer vision and photogrammetry techniques for measurement and defect detection in bridge elements. This is carried out via the processing of images of concrete bridge elements obtained using low-cost drones.

## 1. INTRODUCTION

Due to concentrated periods of development and construction, a significant proportion of built infrastructure is now reaching or is already past their original design life. This results in greater risk of failure and increasing economic costs in terms of preventative maintenance. For example, from about the year 1990, bridge maintenance costs have exceeded construction costs of new bridges in highly industrialised countries (Miyamoto and Motoshita, 2015). Furthermore, as of the year 2021 in the United States, the backlog in bridge rehabilitation costs was estimated at $125 billion (ASCE, 2021). To address these high maintenance costs and reduce bridge rehabilitation backlogs, it is important to implement efficient and effective bridge inspection campaigns as these form the basis of maintenance programs, inform key decision makers and motivate them to prioritise actions. Key aspects for a successful inspection include defect detection, defect documentation and effective communication of information on defects information to the aforementioned decision makers (Collins et al, 2018).

Infrastructure condition assessment has traditionally been carried out by visual inspection; bridge inspectors visually inspect the entire bridge structure at arm's length. Where access is difficult such as where a safe working platform cannot be mounted under bridge decks, or on high bridges, underbridge equipment worth hundreds of thousands of euros or dollars (Wells and Lovelace, 2018) is required and usually results in accompanying expensive lane closures. During this process, a thorough record of all defects such as cracks, spalls, material degradation are manually recorded on inspection forms or the bridge itself, or both. The quality and quantity of the defects recorded during a visual inspection are dependent on the ability of the inspector. However, visual inspections have been shown to lack consistency from inspector to inspector and lack repeatability (Moore et al, 2000).

Approaches supported by technology, including sensor-based condition and assessment methods, have become increasingly popular to obtain more information about a bridge's performance and to assist in addressing the challenges facing traditional approaches. These sensor-based approaches aim to provide information on the static and/or dynamic behaviour of a bridge that allows inspectors to infer the bridge's structural condition. Typically, quantities such as displacement, strain and acceleration are measured using wired or wireless sensing and data acquisition systems, including non-contact optical and infrared (Matsumoto et al 2013) camera-based techniques; the latter offering the potential to directly identify and quantify defects such as cracks. Non-contact and wireless systems have also become commonplace in bridge assessment and monitoring applications as they can hold the advantage of removing, or reducing the need to directly instrument structures, and the requirement for specialist access equipment for visual inspections, thereby reducing the safety risk also.

## 2. UAS IMPLEMENTED BRIDGE INSPECTIONS

In recent years, bridge inspections incorporating unmanned aircraft systems (UASs), or drones, in the inspection process have been advanced as a promising alternative (Zink and Lovelace, 2015). UAS assisted bridge inspections have the dual benefit of implementing non-contact sensing technologies while allowing remote access to difficult regions on a bridge structure. However, there are a number of challenges associated with this and hence research on this topic is growing, in parallel with ever-increasing interest in the technology by hobbyists.

According to the Federal Aviation Administration (FAA) in the United States, in the recent past, hobbyist purchases of drones have increased exponentially with purchases of drones expected to grow from $1.9 million in 2016 to $4.3 million by 2020, while the sale of drones for commercial purposes was expected to grow from $600,000 in 2016 to a potential of $2.7 million by 2020 (FAA, 2016). The overall global market is expected to reach around $58 billion by 2026. As of April 2022, there were almost one million drones registered with the FAA, with around a third of these for commercial operations. In Ireland, the number of drone operators increased by 50% in the calendar year 2022, with this increase also expected to be reflected across Europe.

Ham et al (2016) undertook a review of visual monitoring of civil infrastructure systems via camera-equipped UASs. They note that there has been an exponential growth in the use of UASs equipped with cameras for visual monitoring of construction and operation of civil infrastructure. This rapid rise in the architecture and civil engineering community has been attributed to the equally rapid improvement in UAS technology that has led to UASs being cheaper, more reliable and easier to operate.

Collins et al (2018) evaluated the use of drones for bridge inspections in a four year study and demonstrated that a qualified bridge inspector utilising a drone can improve the ability to detect deficiencies and provide high quality high-resolution digital and infrared images. The use of these types of drones may also reduce the need for expensive access methods and traffic control. Zink and Lovelace (2015) also demonstrated that using collision resistant drones, it is possible to inspect under bridges and in tight and congested areas where flying a drone would be otherwise difficult. It is shown that with these specialised drones, nearly 100 percent inspection coverage of a bridge can be achieved, equipping inspectors with high-resolution imagery for continued offsite defect inspection. These high-resolution images can be further processed into 3D photogrammetry models where defects are recorded, either from the annotations marked on the bridges and photographed, or the inspector can zoom into a region of interest on the model and annotate the defects.

Feroz and Dabous (2021) review UAV (or UAS) based remote sensing applications for bridge infrastructure, highlighting the wide range of literature on the topic and techniques that can be utilized successfully for defect detection, 3D model building, including optical images, LiDAR and infrared thermography. They note the technical challenges and practical limitations associated with UAS approaches, some of which relate to the equipment capabilities, battery power, and data analysis requirements etc. An important challenge is raised regarding the lack of standardized procedures for UAS assisted bridge inspections. This is likely due to the relatively recent development of the body of research in this area; the emergence of a comprehensively validated, reliable and robust common approach is needed to address this, in order to be accepted by the wider community of bridge inspectors, managers and owners. Considering the large volume of data that can generated by UAS assisted bridge inspections, the evolution of existing Bridge Management Systems to a higher level is expected necessary to accommodate this (Habeenzu et al, 2021).

Kim et al (2022) carried out a comparative study of a UAS assisted bridge inspection approach against a conventional human-based approach, carried out on the basis of a UAS-based Bridge Management System (U-BMS), and a deep learning-based damage identification method. The automated UAS based approach was more objective, allowed more accurate measurements of defects such as crack widths (of less than 0.3 mm) and lengths, and was faster; although confirming the best way to incorporate it within a BMS requires further work.

While the state of the art in bridge inspections is promising, at present, a bridge inspector is still required to manually annotate defects. The amount of images produced during a bridge inspection using drones can range from 5 to 50 Gigabytes of data (Wells and Lovelace 2018) which remains a daunting task to manage and sift through to find the required images to annotate accordingly. In fact, this extra time to sift through and process data obtained from a UAS assisted inspection is responsible for increasing costs of UAS assisted inspections compared to traditional approaches. Furthermore, in some cases, the challenge of visual inspection is simply shifted from the bridge site to the computer screen when 3D bridge models are generated. Automated approaches that can automatically detect defects are thus desirable, however, these can also have associated computational time and equipment costs in order to achieve useful results. It is also desirable to reduce the time duration, and hence the associated cost, of this automated post inspection processing. This paper thus presents a simple approach for the automatic annotation of 3D photogrammetric models obtained using a low-cost UAS, with a focus on crack detection and measurement, and briefly summarizes some of the remaining challenges that UAS assisted inspections face.

## 3. METHODOLOGY OF SIMPLE AUTOMATED APPROACH

As 3D photogrammetric models are generated from high quality images, the generated models are large files in the form of point clouds that makes analysis of these models for defects a challenging task for any automated computer algorithm. In this paper, crack defect annotation in 2D images prior to generation of 3D models is explored. The proposed pipeline is shown in Figure 1 below.

The relatively low-cost DJI Spark and Mavic Pro 2 drones are used in this study to capture images of a concrete cube and concrete beam representative sample in the lab. The drones are held by hand and images captured. The relevant drone specifications are summarised in Table 1.

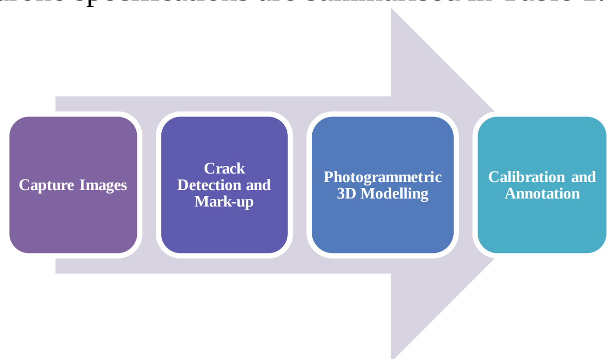



*Figure 1: Annotated 3D model generation workflow.*

*Table 1: Drone specifications*

| |  |  |
|---|---|---|
| Drone | DJI Spark | DJI Mavic Pro 2 |
| Release Date | April 2017 | 21 August 2018 |
| Dimensions (W x H x D) | 143×143×55 mm | 322x242x84 mm |
| Weight | 0.3 kg | 0.9 kg |
| Camera Sensor and resolution | 1/2.3" CMOS Effective pixels: 12 MP | 1-inch CMOS " Effective Pixels: 20 MP |
| Video Resolution | FHD: 1920×1080 30 fps | 1080p video up to 30 fps |
| Field of View | 81.9° | 77° |

### *3.1. Crack detection*

Crack detection is one of the major activities in bridge inspection as deterioration usually manifests itself as cracking. Cracks can be an indication of distress, or the manifestation of material failure, which make a bridge vulnerable to further deterioration, and early failure. Several studies have been conducted to identify cracks from 2D images. The current state of the art uses image intensity thresholding, deep learning algorithms (Kim et al 2022) or machine learning classifiers (Spencer et al 2019). None of these approaches are universally effective and remain active areas of research. This study uses thresholds or edge detection techniques as they are easy to implement using a computer and will suffice for the requirements of this study.

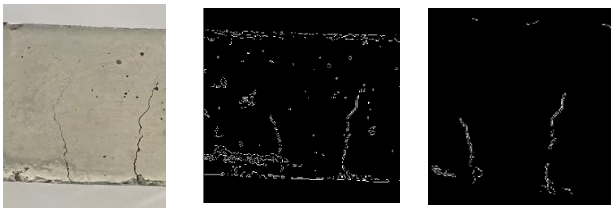
To extract crack features from images, cracks are taken as ‘edges’ where an edge is defined as pixels at which there is an abrupt change in pixel intensity value. Mathematically abrupt changes in intensity values can be detected using derivatives. In image processing this is approximated by the digital difference in the horizontal, vertical and diagonal directions of an image. The digital difference in the horizontal $x$ direction (and similarly in the vertical $y$ direction) is given mathematically as (further details can be found in Gonzalez and Woods (2007)):

$$\frac{\partial y}{\partial x} = f'(x) = f(x+1) - f(x) \qquad (1)$$

More advanced edge detection methods take into account the edge characteristics and noise content of an image. One such method is the Canny edge detector. The Canny edge detector was formulated with three key performance criteria in mind, that is, good detection, good localisation and only one response to a single edge (Canny, 1986). The steps in the Canny edge detector can be summarised as follows:

- Smooth the input image with a Gaussian filter to reduce noise and accentuate edges;
- Compute the gradient magnitude and angle images;
- Apply non-maxima suppression to the gradient magnitude image to retain only the strongest edge response; and
- Use double thresholding and connectivity analysis to detect and link edges.

This results in an edge image with edges only one pixel wide. The canny edge detector is used in this study due to its superiority in localising and detecting edges. As can be seen in Figure 2(b), the process of extracting edges results in noisy images in which unimportant features are detected.



(a) (b) (c)

*Figure 2: (a) Original Image (b) Initial edge detection (c) after classification of crack or non-crack*

One addition pre-processing method is added to the Canny algorithm in this study to reduce the noise. A threshold is employed that limits the greyscale image pixel intensity to a maximum value of two standard deviations below the mean greyscale pixel intensity. A further refinement is employed after edges have been detected by filtering out non-crack like features that: (i) Are smaller than a predetermined pixel length, (ii) have a ratio of major axis to minor axis that approaches to that of a circle, (iii) are completely straight as cracks by nature display a property called tortuosity, that is, they twist and turn. Figure 2(c) shows the improved crack detection after application of the above methods.

### *3.2. Photogrammetry*

The word “photogrammetry" is derived from the three Greek words phos or phot, meaning light; gramma, which means letter or something drawn, and metrein, the noun of measure. It is defined by the American Society for Photogrammetry and Remote Sensing (ASPRS, 2020) as “*the art, science and technology of obtaining reliable information about physical objects and the environment, through processes of recording, measuring and interpreting images and patterns of electromagnetic radiant energy and other phenomena*”.

One of the main algorithms and approaches used to reconstruct the 3D geometry of an object or a scene from 2D images in photogrammetry is structure from motion (SfM). The SfM algorithm aims to derive the 3D scene points and all the camera relative poses from correspondence feature points in multiple overlapping 2D images. Scale ambiguity remains thus the reconstructed scene needs to be scaled to the correct scale after the reconstruction process. When all the camera poses and 3D points and camera poses have been determined, a mesh of the scene is created and textured to create the full 3D model as represented in the 2D images. The full SfM pipeline is summarised in Figure 4 below. In this study, Autodesk Recap Photo was used to create the 3D models.

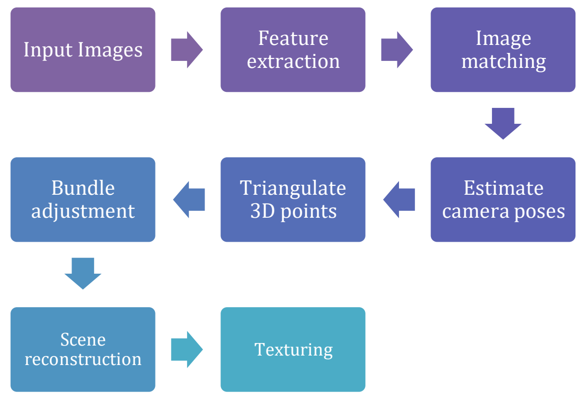



*Figure 3: Structure from motion pipeline*

## 4. EXPERIMENTAL SETUP

A 100x100x100 mm crushed concrete cube and a 65x100x1800 mm cracked concrete beam were used as representative specimens in this study. The concrete cube was used to generate a complete 3D model using images captured by the DJI Mavic 2 Pro while only the beam face was studied using images obtained from the DJI Spark drone. The concrete cube and beam are shown in Figure 5 below. A total of 62 overlapping photos were used for the concrete cube and 39 for the concrete beam.

The edge detection was carried out in MATLAB and the 3D modelling using Autodesk Recap. An HP Envy laptop with an Intel Core i7-5500U (Intel Core i7) processor and NVIDIA GeForce GTX 850M - 4096 MB graphics card was used in this study. To speed up processing time in MATLAB, the image size was reduced by 50% from about 5.2 MB to 2.6 MB for the Mavic 2 Pro and from about 2.8 MB to 1.4 MB for the Spark.

*Figure 4: Test specimens used in this study (a) concrete cube (b) concrete beam*

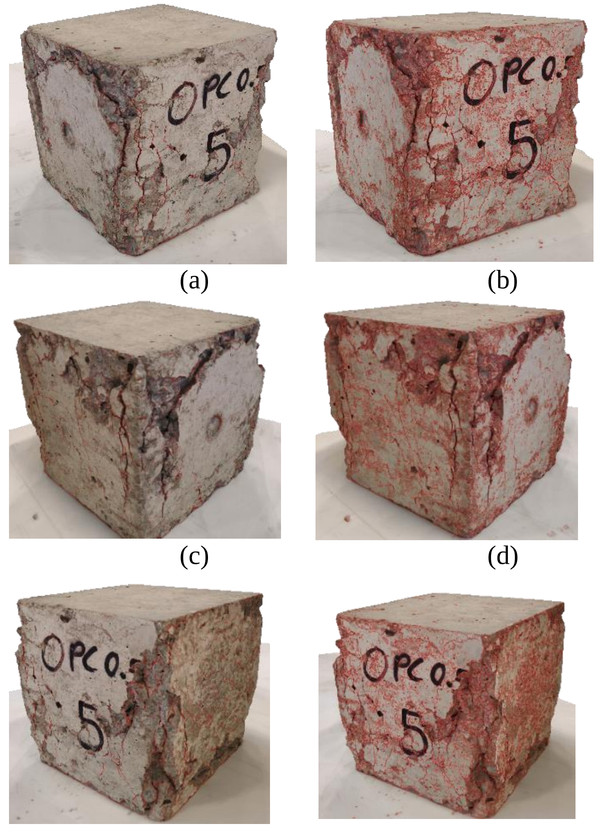
## 5. RESULTS AND DISCUSSION

### *5.1. 3D Modelling and crack detection*

Figure 5 below shows the results of the approach employed in this study for crack detection and annotation on the concrete beam cube. Figures 6 and 7 show the comparison between the approach employed in this study to enhance the output of the Canny edge detector and the Canny edge detection without any enhancement. Note that in both cases the same thresholds were used during hysteresis thresholding (Gonzalez and Woods, 2007).

*Figure 5: Concrete cube 3D model with crack locations marked on the model*

As can be seen from the figures the geometry of the concrete specimens is faithfully reproduced. Furthermore, the crack detection algorithm is able to correctly locate all of the cracks in the concrete beam and many of the cracks in the concrete cube despite the cube having a very noisy texture. The minimum crack width on the concrete beam was measured with a crack gauge to be 0.3 mm.



(a) (b)

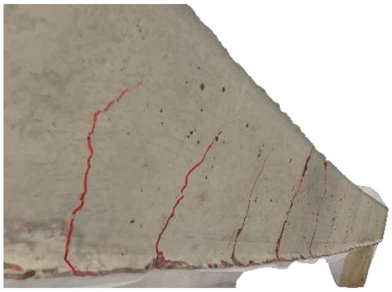
(c) (d)

(e) (f)

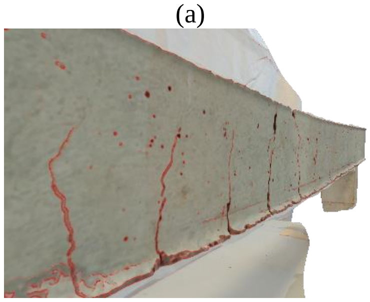
*Figure 6: (a)- (f) Comparison of results of the algorithm employed in this study (left) and ordinary edge detection (right)*

### *5.2. Geometric accuracy of 3D models and crack measurements*

Prior to taking measurements of cracks on the concrete cube, the 3D model was calibrated. As noted in section 3, during modelling there is a scale ambiguity that is not recovered. To correctly scale the model, a scale object such as a ruler is usually fixed on the object to assist with scaling. In this case, the known size of the cube was used to scale and calibrate the dimensions of the 3D model in Autodesk ReCap Photo. Figure 8(a) shows concrete cube with dimension lines marked in ReCap. After calibration, the dimensions of the lines are measured as 98.231 mm.



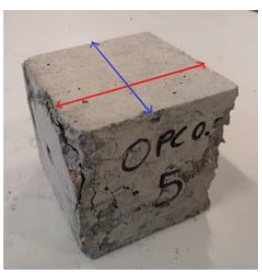
(a)



(b)

*Figure 7: Comparison of crack detection results for (a) the algorithm employed in this study and (b) ordinary edge detection*

Figure 8(b) shows the location used for sample measurement of crack length. Table 2 provides a comparison of measurements obtained in ReCap Photo.



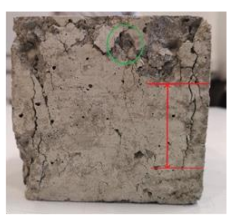



*Figure 8: (a) Calibrating the concrete cube dimensions (b) Crack measurements*

*Table 2: ReCap measurement comparison*

| Feature Measured | Actual Measurement (mm) | ReCap Photo Measurement (mm) | Error (mm) |
|---|---|---|---|
| Dimension | 98 | 98.231 | 0.231 |
| Crack Length | 44 | 44.097 | 0.97 |

From the Table 2, it can be seen that after calibrating and setting distances in the 3D model, very accurate results are obtained with an error of less than 1 mm despite reducing the image resolution by half.

### *5.3. Image Processing time*

The 3D model generation in ReCap was completed via the cloud where for the educational version of the software, there is a waiting period and as a result the actual processing time required could not be determined. The image processing for crack detection using MATLAB took only about 10 seconds per image.

## 6. ONGOING CHALLENGES FOR UAS ASSISTED BRIDGE INSPECTIONS

Improvements in technology that have enabled the investigation of UAS assisted bridge inspections can also result in expensive UAS equipment, cameras, and very complex image processing techniques using multiple UAS, which can require significant computational power and time. While it was not possible to report the image processing time required for the 3D model generation presented in this study with low-cost drones, it remains an active topic of study in terms of improving the computational efficiency with single UAS based approaches. Alongside this, challenges remain in relation to:

- Image stabilization: while current UAS technology enables a relatively stable hover while recording images, measurements remain sensitive to the hovering motion of the UAS which can be in the order of cm, even in calm weather. Stable feature reference points are required within the image frame to correct for the motion – these are not always available in the field. An upcoming publication by the authors presents a solution to this.
- Environmental conditions: The majority of commercially operated and low-cost UAS cannot be operated in windy or wet conditions, thus limiting their applicability. Sunshine and shadows on target structures can also impact measurement quality.
- Limited flight time: most UAS have a limited flight due to payload and battery

capacity, typically in the 14-18 minute range, although this is improving.
- Safety, regulation and privacy concerns: Regulation can lag behind advances in UAS technology which can further delay adoption of validated approaches in BMS.

## 7. CONCLUSIONS

In a UAS assisted bridge inspection, high resolution imagery of nearly 100% of the bridge structure can be obtained and the focus has now shifted from the ability to collect data to making effective use of the data in a low-cost and efficient manner. While a number of challenges remain for widespread adoption and acceptance of UAS for inspections and within updated BMSs, this study has concluded that image processing techniques and photogrammetry can be used together with low-cost UAS to effectively automate the task of detecting cracks and annotating 3D photogrammetric models generated from 2D images.

## 8. ACKNOWLEDGMENTS

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