Towards automated UAV assisted bridge inspections using photogrammetry and image processing techniques

Mr. Habeene Habeenzu[1], Dr Patrick McGetrick[2], Dr David Hester[1], Prof. Su Taylor[1], Mr. Louie Wong[1]
[1]School of Natural and Built Environment, Queen's University Belfast, Belfast, United Kingdom
[2] School of Engineering, National University of Ireland, Galway.
email: hhabeenzu01@qub.ac.uk, patrick.mcgetrick@nuigalway.ie

ABSTRACT: At the heart of addressing bridge condition challenges are bridge inspections. The main activity during a bridge inspection is close, arm's length visual inspection of the entire bridge structure. During this process, all defects such as cracks, spalls and material degradation are manually recorded on the bridge itself and on inspection forms. Where access is difficult such as where a safe working platform cannot be mounted under bridge decks, or on high bridges, expensive underbridge equipment is required which when used results in expensive lane closures. Furthermore, visual inspections have been shown to lack consistency from inspector to inspector and can be unreliable. Technological solutions such as using drones with digital cameras combined with post-processing of images using digital image processing and photogrammetry techniques can potentially assist bridge inspectors in the provision of reliable information on structure geometry, inventory and structure condition, supplementing traditional methods. This information can also be packaged in easy to understand 2D or 3D formats making it more straightforward for bridge owners to make timely decisions about allocating bridge maintenance funds. This paper investigates the use of digital image processing and photogrammetry techniques to detect and annotate 3D models of cracked concrete specimen obtained using drones and presents the results of laboratory tests.

KEY WORDS: Bridge inspection, Crack detection, Image processing, Photogrammetry.

1 INTRODUCTION

From about the year 1990, bridge maintenance costs have exceeded construction costs of new bridges in highly industrialised countries [1] and as of the year 2017 in America for example, the backlog in bridge rehabilitation costs was estimated at $123 billion [2]. To address these high maintenance costs and reduce bridge rehabilitation backlogs, it is important that bridge inspections that form the basis of maintenance programs and inform key decision makers and motivate them to quick action are efficient and effective. Key aspects for a successful inspection include defect detection, defect documentation and effective communication of defects information to decision makers [3]. In traditional bridge inspections, bridge inspectors visually inspect at arm's length the entire bridge structure. 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 dollars [4] 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 either on the bridge itself and/or on inspection forms. The quality and quantity of the defects recorded during a visual inspection is dependent on the ability of the inspector. However, visual inspections have been shown to lack consistency from inspector to inspector and lack repeatability [5]. To address these challenges to traditional approaches, bridge inspections incorporating unmanned aerial vehicles (UAVs) or drones in the inspection process have been advanced as a promising alternative [6].

According to the Federal Aviation Administration (FAA) in the United States, in the recent past, hobbyist purchases of drones has 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 is expected to grow from $600,000 in 2016 to a potential of $2.7 million by 2020 [7]. By 2025, the drone industry is expected to be worth $93 billion [8]. As of January 2018, there were one million drones registered with the FAA. Hammad et al. [9] have undertaken a recent review of visual monitoring of civil infrastructure systems via camera-equipped UAVs. They note that there has been an exponential growth in the use of UAVs 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 to UAV technology that has led to UAVs being cheaper, more reliable, and easier to operate.

Collins et al. [3] 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. Further, the use of these types of drones may also reduce the need for expensive access methods and traffic control. Zink & Lovelace [6] also demonstrated that drones that can be used to inspect under bridges and in tight and congested areas where flying a drone would be difficult using collision resistant drones. They show 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 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 interests on the model and annotate the defects.

While the state of the art in bridge inspections described above is promising, it still requires a bridge inspector to manually annotate defects. The amount of images produced during a bridge inspection using drones can range from 5 to 50 Gigabytes of data [4] 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 drone assisted inspection is responsible for increasing costs of UAV assisted inspections compared to traditional approaches [4]. Further 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 automatically detect defects are thus desirable to reduce the time duration, and hence the associated cost, of this post inspection processing. This paper thus investigates the automatic annotation of 3D photogrammetric models with a focus on crack detection and measurement.

2 PROPOSED METHODOLOGY

2.1 Methodology

As 3D photogrammetric models are generated from high quality images, the generated models are large files in the form of point clouds which 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.

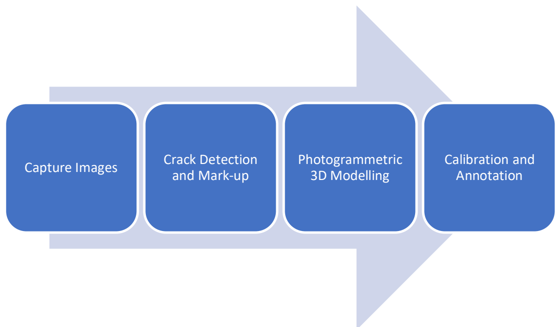


Figure 1. Annotated 3D model generation pipeline.

2.2 Image capture

The 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 are captured. As this paper is a preliminary laboratory study focusing on validating the proposed algorithm for crack detection and markup of 3D photogrammetry models from 2D images, the challenges of taking images with a drone in flight were not the primary objectives of this study. Therefore challenges such as lighting conditions and motion blur are not reported. The relevant drone specifications are summarized in Table 1.

2.3 Crack detection

Crack detection or looking for cracks 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 in 2D images. The current state of the art uses image intensity thresholding or machine learning classifiers [10]. 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 and further, edge detection techniques are still the core of current techniques. In particular the Canny edge detection algorithm is used here as it is superior in terms of having a single edge response as compared to other edge detectors as discussed below.

Table 1. Drone specifications (https://www.dji.com/uk)

		
Drone	DJI Spark	DJI Mavic Pro 2
Cost (12/2019)	£450.00	£1,349
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/resolution	1/2.3" CMOS Effective pixels: 12 MP	1-inch CMOS " Effective Pixels: 20 MP
Video Resolution	FHD: 1920×1080 30fps	1080p video up to 30fps
Field of View	81.9°	77°

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 direction (and similarly in the vertical directions) is given mathematically as:

$$\partial y/\partial x=f'(x)=f(x+1)-f(x) \qquad (1)$$

Replacing x, with y gives the digital difference in the vertical y-direction; further details can be found in [11].

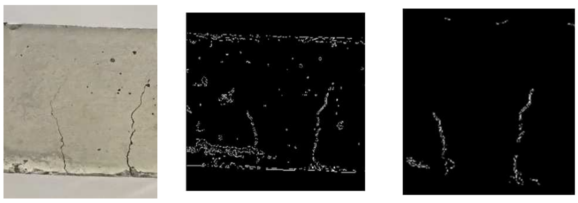
More advanced edge detection methods consider the edge characteristics and noise content of an image. One such method is the Canny edge detector. The Canny edge detector was formulated with three key performance criteria in mind, that is, good detection, good localisation and only one response to a single edge [12].

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, the process of extracting edges results in noisy images in which features which are not of interest 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 which limits the greyscale image pixel intensity to a maximum value of two standard deviations below the mean grayscale pixel intensity is employed. A further refinement is employed after edges have been detected by filtering out of non-crack like features by defining non- crack features as those that:

1. Are smaller than a predetermined pixel length;
2. Have a ratio of major axis to minor axis that approaches to that of a circle;
3. 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.

2.4 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 [13]. It is defined by the American Society for Photogrammetry and Remote Sensing (ASPRS) 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." [14]

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 [15], see Figure 3.

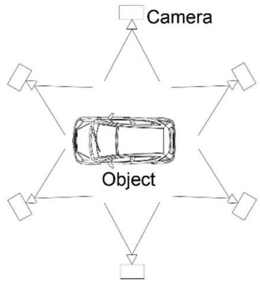


Figure 3. Capturing overlapping images

Given calibrated point projections of p = 1…N points in f=1… F camera frames, it is required to find the 3D rigid rotation and translation transformations, R^f, T^f and the 3D object points, X_p, Y_p, Z_p that closely fulfil the projection equations:

$$x_p^f = \frac{R_{11}^f X_p + R_{12}^f Y_p + R_{13}^f Z_p + T_x}{R_{31}^f X_p + R_{32}^f Y_p + R_{33}^f Z_p + T_z} \quad (2)$$

$$y_p^f = \frac{R_{21}^f X_p + R_{22}^f Y_p + R_{23}^f Z_p + T_y}{R_{31}^f X_p + R_{32}^f Y_p + R_{33}^f Z_p + T_z} \quad (3)$$

The solution to these equations is a nonlinear least squares optimisation of a cost function known as the total reprojection error; see [16] for further details. Note that the scale ambiguity remains and as such 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.

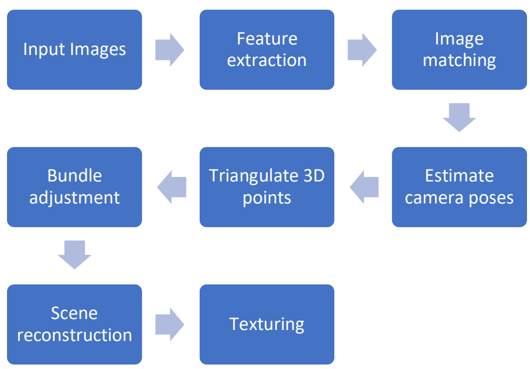


Figure 4. Structure from motion pipeline

In this study, Autodesk Recap Photo was used to create the 3D models.

3 EXPERIMENTAL SETUP

A 100x100x100 mm crushed concrete cube and a 65x100x1800 mm long 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 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 half from about 5.2MB to 2.6MB for the Mavic and from about 2.8MB to 1.4MB for the Spark.

Figure 5. Specimen used in this study (a) concrete cube (b) concrete beam

4 RESULTS AND DISCUSSION

4.1 3D Modelling and crack detection

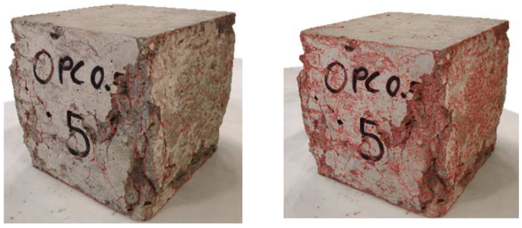
Figure 6 below shows the results of the approach employed in this study for crack detection and annotation on the concrete beam cube. Figures 7 and 8 show the comparison between the approach employed in this study to enhance the output of the Canny edge detector and the Canny edge detection without any enhancement. Note that both cases use the same thresholds during hysteresis thresholding [11].

Figure 6. 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. Further the crack detection algorithm can correctly locate all 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.

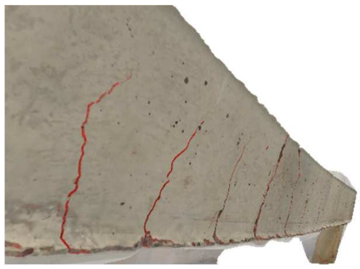
(a) (b)

(c) (d)

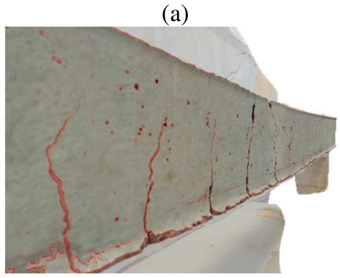


(e) (f)

Figure 7 (a)- (f), Comparison of results of the algorithm employed in this study (left) and ordinary edge detection (right)



(a)



(b)

Figure 8 (a), (b) Comparison of results of the algorithm employed in this study (left) and ordinary edge detection (right)

4.2 Geometric accuracy of 3D models and crack measurements

Before taking measurements of cracks on the concrete cube, the model was first calibrated. As noted in section 3.1, 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 3D model in Autodesk ReCap Photo. Figure 9 (a) shows concrete cube with red and blue lines marked in ReCap. After calibration, the dimensions of the lines were measured as 98.231 mm.

Figure 9 (a) Calibrating the concrete cube (b) Crack measurements

Figure 9 (b) shows a sample measurement for crack length. the areas where we measured for crack length. Table 2 below shows the comparison of measurements obtained in ReCap Photo.

Table 2. ReCap measurement comparison

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

From the table of results above, 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.

4.3 Image Processing time

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

5 CONCLUSIONS

When using a UAV assisted bridge inspection, high resolution imagery of nearly 100% of the bridge can be obtained and the focus has now shifted from the ability to collect data to making effective use of the data [4]. This study has concluded that image processing techniques and photogrammetry can be used together to effectively automate the task of detecting cracks and annotating 3D photogrammetric models generated from 2D images obtained using drones.

ACKNOWLEDGMENTS

The authors wish to express their gratitude to the Commonwealth Scholarship Commission in the UK for the funding received in support of this research.

REFERENCES

[1] A. Miyamoto and M. Motoshita, “Development and Practical Application of a Bridge Management System (J-BMS) in Japan,” *Civ. Eng. Infrastructures J.*, vol. 48, no. 1, pp. 189–216, 2015, doi: 10.7508/ceij.2015.01.013.

[2] ASCE, “2017 Infrastructure Report Card.” [Online]. Available: https://www.infrastructurereportcard.org/cat-item/bridges/.

[3] T. Collins, B. Lovelace, and J. Wells, “The Effectiveness of Unmanned Aerial Systems For Bridge Inspections,” in *Civil Engineering Research in Ireland 2018 (CERI 2018)*, 2018, pp. 19–34.

[4] J. Wells and B. Lovelace, “Improving the Quality of Bridge Inspections Using Unmanned Aircraft Systems (UAS),” *Minnesota Dep. Transp.*, no. MN/RC 2018-26, pp. 1–345, 2018, [Online]. Available: http://www.dot.state.mn.us/research/reports/2018/201826.pdf.

[5] M. Moore, B. Phares, B. Graybeal, D. Rolander, and G. Washer, “Reliability of Visual Inspection for Highway Bridges (FHWA-RD-01-020),” vol. II, no. FHWA-RD-01-020, 2000, [Online]. Available: http://www.tfhrc.gov/hnr20/nde/01020.htm.

[6] J. Zink and B. Lovelace, “Unmanned Aerial Vehicle Bridge Inspection Demonstration Project,” no. July, p. 214, 2015, doi: 10.1016/j.ceramint.2011.07.049.

[7] Federal Aviation Administration, “FAA Releases 2016 to 2036 Aerospace Forecast,” 2016. https://www.faa.gov/news/updates/?newsId=85227 (accessed Mar. 25, 2019).

[8] Teal Group Corporation, “UAV Production Will Total $93 Billion - Teal Group,” 2015. https://www.tealgroup.com/index.php/pages/press-releases/34-uav-production-will-total-93-billion (accessed Mar. 25, 2019).

[9] Y. Ham, K. K. Han, J. J. Lin, and M. Golparvar-Fard, “Visual monitoring of civil infrastructure systems via camera-equipped Unmanned Aerial Vehicles (UAVs): a review of related works,” *Vis. Eng.*, vol. 4, no. 1, pp. 1–8, 2016, doi: 10.1186/s40327-015-0029-z.

[10] B. F. Spencer, V. Hoskere, and Y. Narazaki, “Advances in Computer Vision-Based Civil Infrastructure Inspection and Monitoring,” *Engineering*, vol. 5, no. 2, pp. 199–222, 2019, doi: 10.1016/j.eng.2018.11.030.

[11] R. C. Gonzalez and R. E. Woods, *Digital Image Processing (3rd Edition)*. Pearson, 2007.

[12] J. Canny, “A Computational Approach to Edge Detection,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-8, no. 6, pp. 679–698, 1986, doi: 10.1109/TPAMI.1986.4767851.

[13] “Geography word of the week: photogrammetry | Canadian Geographic.” https://www.canadiangeographic.ca/article/geography-word-week-photogrammetry (accessed May 20, 2020).

[14] “ASPRS – IMAGING AND GEOSPATIAL SOCIETY.” https://www.asprs.org/ (accessed May 21, 2020).

[15] W. (Wolfgang) Förstner and B. P. Wrobel, *Photogrammetric computer vision : statistics, geometry, orientation and reconstruction*. .

[16] O. Özyeşil, V. Voroninski, R. Basri, and A. Singer, “A survey of structure from motion,” *Acta Numer.*, vol. 26, pp. 305–364, 2017, doi: 10.1017/S096249291700006X.