An Integrated Unmanned Aerial Vehicle-Based Framework for Crack Detection and Classification of Bridge Infrastructure

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Abstract – Bridge infrastructure is highly susceptible to deterioration due to continuous exposure to harsh environmental conditions and increasing traffic volumes and loads, necessitating frequent inspections to ensure structural safety and serviceability. Traditional bridge inspection approaches are often time-consuming, labor-intensive, error-prone, and disruptive to traffic operations, highlighting the need for more efficient, reliable, and non-invasive inspection solutions. Although several studies have proposed sensor-based and unmanned aerial vehicle (UAV)-assisted inspection systems, limited research has focused on the systematic identification, classification, and quantitative assessment of surface crack severity using image-based approaches. To address this gap, this study develops an integrated UAV-based framework for automated crack detection and classification within a bridge monitoring system. The proposed framework advances existing approaches through the integration of crack identification using gray-scale pixel-based image analysis and crack classification based on geometry, orientation, and severity. The methodology comprises four main stages: UAV-based data acquisition, image preprocessing and crack detection, quantitative crack characterization and classification, and validation through laboratory testing and a real-world bridge case study. Preliminary case study results show that the proposed gray-scale pixel-based algorithm achieves minimum errors of 2.9% and 5.5% and maximum errors of 17.9% and 16.0% for crack length and width estimation, respectively. Severity classification was consistent for moderate and extended cracks (2 out of 4 segments), while fine cracks exhibited higher misclassification rates due to reduced contrast and image quality. Orientation profiling showed correct or partial agreement for most detected crack segments. Higher errors under real-world conditions highlight the need for improved image acquisition stability.

Keywords–Digital Inspection; Computer Vision; Structural Health Monitoring (SHM); Automated Quantification; Human Robot Interaction (HRI); Infrastructure Resilience Assessment.

1 Introduction

Bridge infrastructure is a critical component of highway transportation systems and plays a vital role in ensuring connectivity, safety, and economic development. Due to continuous exposure to harsh environmental conditions, heavy traffic, and aging, bridges are highly susceptible to deterioration and damage, necessitating regular inspection and maintenance [1,2]. However, transport authorities often operate under strict time and budget constraints, which limit the effectiveness and frequency of traditional inspection practices [1]. Conventional bridge inspection processes rely primarily on visual and manual inspection, making them labor-intensive, time-consuming, subject to personal judgment, and potentially dangerous for inspectors [3]. In addition, these inspections often require road closures and may fail to identify hard-to-reach or hidden defects, resulting in incomplete condition assessments [4]. To address these limitations, recent research has increasingly focused on non-contact and non-destructive testing (NDT) technologies for bridge inspection and monitoring, including photogrammetry, infrared thermography, and unmanned aerial vehicles (UAVs) [5,6]. Infrared thermography has also been used in combination with machine learning techniques to estimate crack properties such as crack width from temperature variations captured in thermal images [7]. Among these technologies, UAV-based inspection has received considerable attention due to its ability to safely access difficult-to-reach locations, reduce inspection time and cost, minimize traffic disruption, and provide high-resolution visual data for structural assessment [4,8]. UAV-mounted visual imaging systems have been widely applied for crack detection, surface damage identification, and geometric measurements of bridge elements, with several studies reporting accuracy comparable to that of conventional field measurements [9]. UAV-based images further enable the reconstruction of three-dimensional (3D) models from overlapping images, supporting improved localization and quantitative assessment of surface defects [10]. Photogrammetry-based approaches have been successfully applied to generate textured 3D models of concrete elements and extract crack characteristics such as crack length, width, and deformation behavior from image data [11]. Previous studies have demonstrated the potential of UAV imagery for crack detection, deformation monitoring, corrosion assessment, and post-disaster damage evaluation of bridge infrastructure [12]. Despite these advances, UAV-based inspection approaches remain sensitive to imaging conditions such as lighting variability, image blur, and surface texture, which can affect the reliability of crack detection and measurement [13]. At the same time, significant efforts have been made to automate the crack detection using image processing and computer vision techniques. Traditional image-based methods rely on filtering, thresholding, edge detection, and morphological operations to extract crack features and estimate their dimensions [14]. More recently, artificial intelligence and deep learning approaches have been introduced to improve detection accuracy under changing environmental conditions [15]. However, such data-driven methods typically require large, well-labeled datasets and extensive training, which are often unavailable in practical bridge inspection scenarios.

Moreover, many existing crack detection approaches primarily focus on identifying the presence of cracks rather than systematically characterizing crack geometry and orientation [16]. In particular, limited attention has been given to extracting quantitative crack properties such as crack length, width, and orientation while simultaneously interpreting crack patterns relative to bridge components and infrastructure condition assessment. Such detailed crack characterization is essential for supporting maintenance planning and structural evaluation of bridge infrastructure.

1.1 Research Gaps

Despite significant progress in UAV-based bridge inspection, several research gaps remain in the current literature. First, many existing studies focus on individual techniques or standalone inspection methods and lack integrated, image-based frameworks that support systematic crack identification, profiling, and quantitative assessment within an automated and updatable bridge monitoring workflow [17]. Second, while crack detection has been widely investigated, limited attention has been given to extracting and utilizing gray-scale pixel-level information for robust crack identification and quantitative characterization of crack properties such as length, width, and orientation.

Finally, most existing UAV-based crack detection approaches emphasize automated detection but rarely incorporate systematic analysis of crack orientation patterns or their relationship with specific bridge components [13]. The geometric orientation of cracks, such as horizontal, vertical, and diagonal patterns, can provide valuable insight into potential structural behavior and deterioration mechanisms. However, this contextual interpretation is often missing in existing automated inspection frameworks. Therefore, there remains a need for integrated methodologies that combine crack identification, quantitative crack characterization, and orientation-based crack profiling to support practical bridge inspection and maintenance decision-making.

1.2 Objectives and Contributions

To address the identified research gaps, this study aims to develop a UAV-based bridge monitoring framework using image-based techniques for crack detection and assessment. A UAV-based image analysis approach is implemented for concrete highway bridges to support surface crack detection, characterization, and classification. Unlike many existing UAV inspection approaches that rely heavily on deep learning models requiring large labeled datasets, the proposed framework utilizes gray-scale pixel-based image analysis to detect crack features and extract their geometric properties. The methodology integrates crack detection with quantitative characterization of crack attributes and orientation-based profiling to enable a more comprehensive interpretation of crack patterns relevant to bridge infrastructure assessment. The specific objectives of this study are to 1) develop a gray-scale pixel-based approach for identifying surface cracks from UAV-acquired images; 2) extract quantitative crack characteristics, including length, width, and orientation, from detected crack features; and 3) profile cracks based on their geometric orientation (horizontal, vertical, and diagonal) to support systematic assessment of bridge infrastructure; 4) determine crack severity levels (e.g., low, moderate, and extended) by integrating gray-scale crack identification and geometric crack profiling results to support condition assessment of bridge components. The main contribution of this study lies in the development of an integrated UAV-based inspection framework that combines gray-scale image analysis with orientation-based crack profiling and quantitative crack characterization within a unified monitoring workflow. This approach enables systematic crack assessment without relying on extensive training datasets typically required by deep learning models. The methodology is verified through a real-world bridge case study conducted in the United Arab Emirates (UAE), demonstrating its applicability to automated, non-invasive bridge inspection.

2 Materials and Methods

This study develops a UAV-based image analysis methodology for bridge condition assessment focused on surface crack detection and characterization. UAV-assisted inspection provides a non-contact and non-invasive means of acquiring high-resolution visual data, enabling access to hard-to-reach bridge components while reducing inspection time, cost, and traffic disruption. The proposed framework follows a sequential, image-driven workflow, as illustrated in Figure 1, consisting of six main actions: acquiring UAV images, detecting surface cracks, extracting crack geometry, profiling crack orientation, classifying crack severity, and supporting informed inspection and maintenance decision-making. First, high-resolution images of bridge components are acquired using a UAV under controlled environmental conditions to ensure adequate image quality. Second, the acquired images are directly processed using a gray-scale pixel-based crack detection algorithm to identify potential crack regions. Third, quantitative crack geometry, including crack length and width, is extracted from the detected crack features. Fourth, cracks are profiled based on their geometric orientation as horizontal, vertical, or diagonal. Fifth, crack severity levels are determined by integrating crack geometry and orientation information to distinguish between minor and more critical surface defects relevant to bridge inspection. Finally, the extracted crack characteristics are used to support systematic interpretation of bridge surface condition and inform inspection and maintenance considerations.

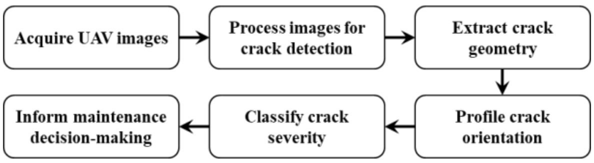

Figure 1. Research methodology framework

2.1 Acquire UAV Images

The data acquisition stage focuses on collecting sufficient high-resolution visual information to support reliable image-based crack detection and quantitative crack characterization of bridge surface defects. UAVs are employed to capture high-resolution, overlapping images of bridge components from multiple viewpoints, ensuring adequate coverage and redundancy for image processing and crack analysis [10,18]. Careful flight planning is undertaken to achieve appropriate image overlap, viewing angles, and spatial resolution required for reliable crack identification and measurement. Data acquisition planning considers environmental conditions, including lighting variability, wind speed, and operational constraints, to minimize image blur and distortion during flight. Particular attention is given to capturing close-range images of critical structural components to support gray-scale, pixel-based crack identification and the subsequent extraction of crack characteristics, such as length, width, and orientation.

2.2 Process Images for Crack Detection

The acquired UAV images are directly processed using image processing techniques without relying on 3D surface reconstruction. Images are converted to gray-scale format and analyzed based on pixel intensity variations to enhance crack features relative to the surrounding surface texture. Preprocessing operations, including noise suppression and contrast enhancement, are applied to reduce the influence of illumination variability and background irregularities. This processing stage establishes a consistent basis for crack detection by improving the separability of crack pixels from non-crack regions. The processed images are then prepared for segmentation, enabling reliable identification of crack features across different bridge components and imaging conditions.

2.3 Extract Crack Geometry

Following crack detection, quantitative crack geometry is extracted from the segmented crack regions. Crack length is computed based on the spatial extent of detected crack features, while crack width is estimated using pixel-based geometric analysis techniques. These measurements provide objective and repeatable metrics for characterizing crack extent and severity. The extracted geometric properties form the quantitative foundation for crack profiling and severity classification. By relying on gray-scale pixel information and geometric measurements, the methodology enables consistent crack characterization without the need for prior training data or complex learning-based models.

2.4 Profile Crack Orientation

Detected cracks are subsequently profiled according to their geometric orientation and classified as horizontal, vertical, or diagonal. Orientation profiling is performed by analyzing the spatial alignment of crack features relative to the image coordinate system. This classification supports systematic comparison of crack patterns across different bridge components and aids in interpreting crack behavior with respect to structural configuration, as different crack orientations may be associated with different damage mechanisms or structural responses. In addition to orientation profiling, crack severity is classified into three discrete levels, namely fine, moderate, and extended, based on quantitative crack width measurements. These severity categories are defined using width thresholds commonly adopted in bridge inspection practice, enabling consistent differentiation between less critical and more significant surface defects. The combined use of crack orientation and severity classification provides contextual information essential for systematic condition assessment of bridge infrastructure.

2.5 Classify Crack Severity

Crack severity is classified by integrating quantitative crack geometry and orientation information. Severity is defined using three discrete categories, namely fine, moderate, and extended, which are determined primarily based on crack width thresholds commonly adopted in bridge inspection practice [14], enabling differentiation between less critical and more significant surface defects. The integration of crack geometry and orientation supports a structured and interpretable severity assessment framework. This classification approach facilitates consistent evaluation of crack conditions across bridge elements and supports prioritization of defects that may require closer inspection or maintenance intervention.

2.6 Inform Maintenance Decision-Making

The combined outputs of crack detection, geometric extraction, orientation profiling, and severity classification are used to inform the interpretation of bridge surface condition. By providing quantitative and contextual crack information, the proposed methodology supports inspection reporting and maintenance planning, enabling engineers and asset managers to better understand defect characteristics and their potential implications. Although the framework does not replace engineering judgment, it provides a transparent and systematic basis for supporting inspection decisions and identifying areas that may require further investigation or monitoring.

3 Methodology Implementation

This section presents the implementation of the proposed methodology described in Section 2. The methodology is applied to a real-world bridge case study to demonstrate its practicality and effectiveness for bridge condition assessment. The implementation includes site reconnaissance, UAV-based data acquisition, execution of the image-based crack detection and quantification process, and validation through laboratory testing and field application.

3.1 Site Reconnaissance

A prestressed concrete highway bridge located in Ghalilah, Ras Al Khaimah, UAE, was selected to implement and evaluate the proposed UAV-based bridge inspection methodology. The bridge is located along the E11 highway and comprises four traffic lanes supported by six simply supported spans, each 11.5 m long, resulting in a total length of 71 m and a vertical clearance of approximately 9.1 m. The superstructure consists of a precast reinforced concrete deck supported by cast-in-place concrete piers and closed abutments with wingwalls, with expansion joints, parapets, and safety barrier railings provided along the deck edges. The bridge was selected due to the availability of historical inspection reports, which supported validation of the proposed methodology, as well as its representative lighting conditions and limited surrounding obstructions. The inspection records were reviewed to obtain information on structural characteristics, component geometry, and previously reported defects, aiding UAV flight planning and identification of damage-prone areas. As shown in Figure 2, reported defects included concrete efflorescence, spalling, and vertical and horizontal cracking on the bridge deck. A site reconnaissance survey was conducted to identify potential hazards to UAV operations, including traffic flow and nearby obstructions, and to determine suitable take-off and landing locations. A preliminary visual inspection was also performed to identify bridge elements requiring close-range UAV imaging. Required approvals for UAV operation were obtained from the relevant authorities, and pre-flight checks were conducted in accordance with regulatory and manufacturer guidelines to ensure safe UAV operation during data acquisition.

Figure 2. Condition of the bridge structure extracted from inspection reports

3.2 Acquire UAV Images

A UAV-based data acquisition strategy was adopted to capture high-resolution images suitable for image-based crack analysis. Data collection was conducted under favorable environmental conditions, including sufficient lighting, low wind speeds, and moderate ambient temperatures. A DJI Inspire 2 quadcopter vertical take-off and landing (VTOL) UAV equipped with a Zenmuse X7 camera featuring a 24-megapixel, 35-mm sensor was used for image acquisition. Live video streaming provided a first-person view of the UAV trajectory and enabled real-time identification of areas requiring additional inspection. Due to proximity to structural elements and the presence of GPS-denied environments beneath the bridge deck, the UAV was operated in manual flight mode with approximately 80% horizontal overlap. Manual operation allowed adaptive flight-path adjustment and improved control during close-range imaging. The UAV was flown at an average distance of approximately 2m from the bridge surface with an inclination angle of about 15º. An initial flight focused on imaging the underside of the bridge deck, followed by two additional flights targeting cracked and spalled regions identified during site reconnaissance. In total, 64 high-resolution images and two video sequences were acquired for subsequent analysis.

3.3 Process Images for Crack Detection

The acquired UAV images were processed using MATLAB®-implemented image processing algorithms. Images were directly analyzed without three-dimensional reconstruction. Each image was loaded into the processing interface, where resizing was applied as required to reduce computational demand. Image preprocessing included smoothing, Gaussian filtering, and adaptive histogram equalization to suppress noise, reduce image disturbances, and enhance contrast while limiting amplification of background noise.

Primary segmentation was performed using gray-scale thresholding to convert the image into a binary representation, highlighting potential crack regions. A global gray-scale threshold was applied to separate dark crack pixels from the surrounding concrete surface based on pixel intensity differences following preprocessing operations. The threshold value was determined empirically during algorithm calibration to enhance crack visibility while suppressing background noise. In the context of the conducted experiments, the fine-tuned gray-scale threshold value was set to 90, based on empirical calibration across representative sample images, where threshold values between 70 and 120 were evaluated to achieve optimal separation between crack pixels and background intensity levels. Secondary segmentation employed an active contour region-growing approach to refine crack boundaries and separate crack features from the background.

3.4 Extract Crack Geometry

Post-processing operations were applied to reduce false detections, including area-based filtering to remove small, isolated segments and mean-intensity-based dark-blob filtering to eliminate regions insufficiently distinct from the background. Following post-processing, quantitative crack geometry was extracted from detected crack segments. Crack length was determined using skeletonization, which extracts crack centerlines while preserving topological continuity. Crack width was estimated using a distance transform approach, whereby distances from crack boundaries to the centerline were averaged and converted to physical dimensions. These geometric measurements provided objective metrics for crack characterization. Based on the laboratory validation results, the smallest crack width successfully detected during laboratory validation was approximately 0.72 mm under controlled imaging conditions. Under field conditions, the effective detectable crack width may increase due to image resolution limitations, UAV vibration, lighting variability, and perspective distortions during image acquisition.

3.5 Profile Crack Orientation and Classify Crack Severity

Detected cracks were profiled based on geometric orientation and classified as horizontal, vertical, or diagonal according to predefined angular thresholds. Crack segments with orientation angles less than 30° or greater than 150º were classified as horizontal cracks. Segments with angles between 30º and 70º or between 110º and 150º were classified as diagonal cracks, while remaining orientations were classified as vertical cracks.

Crack severity was subsequently classified by integrating crack width measurements with predefined severity categories. Crack width thresholds were defined as fine cracks (0.1-1 mm), moderate cracks (1-5 mm), and extended cracks (>5 mm), consistent with commonly adopted bridge inspection practices [19].

3.6 Inform Maintenance Decision-Making and Validation

The extracted crack geometry, orientation profiles, and severity classifications were used to inform the interpretation of bridge surface condition. By providing quantitative and contextual crack information, the methodology supports inspection reporting and identification of areas requiring closer monitoring or intervention. Validation was performed at both laboratory and field scales. Laboratory validation used four concrete beam specimens (50×15×15cm) with vertical cracks induced through four-point flexural testing. Crack dimensions were measured using an electronic handheld digital microscope with a maximum magnification of 1600x, and corresponding images were captured under controlled conditions (Figure 3).

Figure 3. Images of cracked beam: A) specimen 1, B) specimen 2, C) specimen 3, and D) specimen 4

The crack delineation results obtained using the MATLAB®-based algorithm are illustrated in Figure 4. In all specimens, the algorithm successfully identified crack segments. Minor background noise, including surface discoloration, markings, and small spalled regions, was occasionally misclassified as cracks. However, these artifacts were excluded through manual refinement. Manual intervention was primarily required to remove false-positive regions and recover crack segments that were partially undetected due to low image contrast or segmentation discontinuities. In the laboratory validation stage, manual refinement was limited to excluding a small number of non-crack segments, representing less than approximately 10% of detected regions. This indicates that the majority of crack detection and geometric characterization was performed automatically by the algorithm, while manual intervention was limited to correcting segmentation artifacts and refining crack boundaries. The algorithm correctly identified crack orientation in all laboratory specimens. Quantitative validation results indicate that crack length and width estimation errors were less than 17.9% and 16.0%, respectively. Specimen 3 exhibited the highest accuracy, with errors of 2.9% for crack length and 5.5% for crack width. In contrast, specimen 4 exhibited the most significant errors, highlighting the increased difficulty in identifying very fine cracks that exhibit limited contrast relative to background noise. These results indicate that uncertainty in crack detection arises from several factors, including image resolution, crack visibility relative to background texture, segmentation threshold sensitivity, and UAV image acquisition stability. In particular, motion-induced image blur and non-perpendicular viewing angles may reduce the detectability of fine cracks and introduce measurement uncertainty in crack geometry estimation.

A comparison between measured and estimated crack dimensions is provided in Table 1.

Table 1. Comparison of measured and estimated crack dimensions

Specimen #		Original	Estimated	Percent Error (%)
1	Length (cm)	16.100	16.710	**3.789**
2		16.700	17.395	**4.162**
3		18.200	18.742	**2.978**
4		6.300	5.171	**17.921**
1	Width (cm)	0.280	0.251	**10.357**
2		0.100	0.092	**8.000**
3		0.072	0.076	**5.556**
4		0.025	0.029	**16.000**

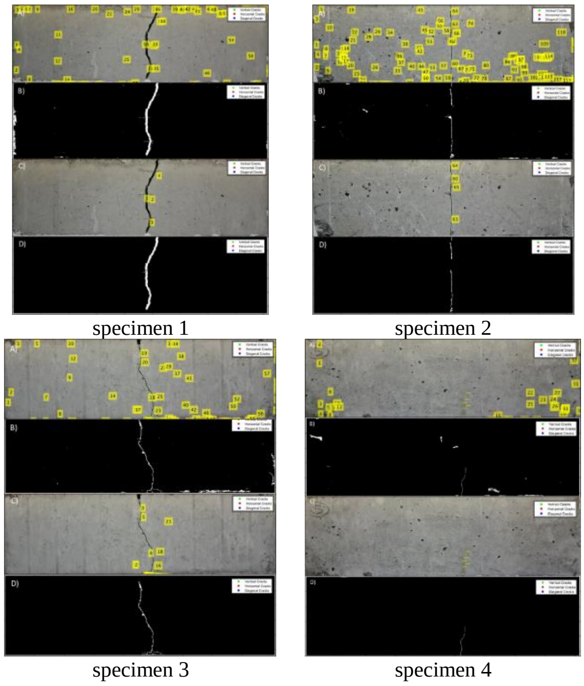

Figure 4. Overlay and binarized crack detection results for laboratory specimens before and after manual enhancement.

Following laboratory validation, the crack detection algorithm was applied to UAV-acquired images of the bridge deck. Visual inspection identified multiple cracks within an approximately 80×100cm region of the deck surface. As shown in Figure 5, diagonal fine cracks were observed in segments 1 and 2, a vertical extended crack in segment 3, and a horizontal moderate crack in segment 4. This image region is presented as a representative example to illustrate the implementation of the proposed crack detection and classification methodology. The algorithm was applied to several UAV-acquired images collected during the inspection campaign; however, the selected region was used to demonstrate the step-by-step crack detection process and the interpretation of crack geometry, orientation, and severity classification results.

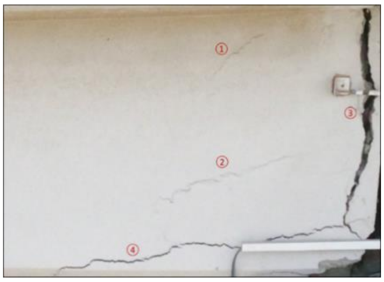

Figure 5. Cracks identified on an image of the bridge deck extracted using a UAV

Automated crack detection results are presented in Figure 6. Initial segmentation results revealed incomplete crack delineation and misclassification of certain background elements as cracks, particularly in regions containing fine cracks. Manual refinement was therefore performed by marking undetected crack regions and excluding background elements such as cables and spalled areas. Manual adjustments were required primarily for two of the four crack segments detected in the case study, particularly for fine cracks where contrast between crack features and surrounding concrete surfaces was limited. The initial identification and geometric extraction of crack features were performed automatically by the algorithm, while manual refinement was applied only to correct segmentation artifacts and improve crack continuity in challenging regions. Despite these adjustments, some crack segments remained partially disconnected due to image blur and non-perpendicular viewing angles during image acquisition.

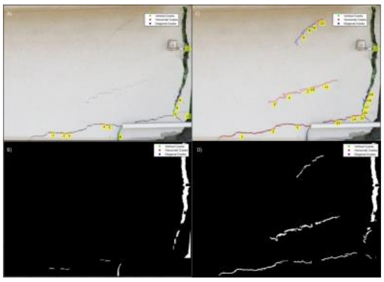

Figure 6. Images obtained from crack detection analysis, showing automatic segmentation and corresponding overlay results before and after manual refinement.

The dimensional statistics reported by the algorithm are summarized in Table 2. Crack segments 3 and 4 were correctly classified in terms of both orientation and severity, while segments 1 and 2 were misclassified as moderate cracks and partially misidentified as horizontal cracks. These discrepancies are attributed primarily to UAV vibration, image blur, and perspective distortion, which reduced crack visibility and contrast in fine and moderate crack regions.

Table 2. Comparison of crack dimensions, orientation, and severity

Segment	Width	Height	Dimension		Orientation	
#	(mm)	(mm)	Original	Classified	Original	Classified
1	3.87	223.08	Fine	Moderate	Diagonal	Horizontal / Diagonal
2	4.93	403.94	Fine	Moderate	Diagonal	Horizontal
3	7.32	646.02	Extended	Extended	Vertical	Vertical
4	3.87	750.17	Moderate	Moderate	Horizontal	Horizontal

4 Conclusions and Future Work

This study presented a proof-of-concept UAV-based bridge inspection framework for crack assessment that integrates gray-scale pixel-based crack detection, geometric characterization, and severity classification. The framework was implemented and evaluated through preliminary laboratory experiments and a real-world bridge case study in the UAE to demonstrate its feasibility and practical applicability under controlled and field conditions.

The preliminary results indicate that the proposed image-based approach is capable of identifying crack geometry, orientation, and severity trends, with acceptable accuracy under laboratory conditions and increased uncertainty under real-world imaging constraints. These findings highlight both the potential and current limitations of UAV-acquired imagery for detailed crack assessment, particularly when image clarity and acquisition stability are affected. Sources of uncertainty include variations in lighting conditions, image blur caused by UAV vibration, surface texture variability, and perspective distortion during image acquisition. These factors may affect the reliability of crack segmentation and introduce uncertainty in crack geometry estimation, particularly for very fine cracks. Based on the laboratory validation results, the smallest crack width successfully detected using the proposed methodology was approximately 0.72 mm under controlled imaging conditions. However, under field conditions, the effective detectable crack width may increase due to image resolution limitations and environmental factors affecting image clarity.

By combining crack geometry and orientation profiling with severity classification, the framework supports context-aware interpretation of surface cracks relevant to bridge components and inspection reporting. The methodology, therefore, provides a structured and transparent basis for identifying crack patterns and prioritizing areas that may require closer inspection or maintenance intervention.

Overall, the proposed methodology demonstrates the feasibility of a non-invasive, image-driven approach for UAV-based bridge inspection and provides a foundation for more comprehensive and robust implementations. Although the presented results focus on a representative example image region to illustrate the methodology, further validation using larger annotated image datasets would enable more comprehensive statistical evaluation of detection and classification performance. Future research will therefore focus on expanding the dataset and incorporating quantitative performance metrics such as precision, recall, and confusion matrices to provide a more rigorous assessment of algorithm performance.

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References

[1] S. Abu Dabous and S. Alkass, Managing bridge infrastructure under budget constraints: A decision support methodology, *Can. J. Civ. Eng.*, vol. 38, no. 11, pp. 1227–1237, 2011, doi: 10.1139/l11-082.

[2] W. Cook, P. J. Barr, and M. W. Halling, Bridge Failure Rate, *J. Perform. Constr. Facil.*, vol. 29, no. 3, p. 04014080, Dec. 2015, doi: 10.1061/(asce)cf.1943-5509.0000571.

[3] D. Agdas, J. A. Rice, J. R. Martinez, and I. R. Lasa, Comparison of Visual Inspection and Structural-Health Monitoring As Bridge Condition Assessment Methods, *J. Perform. Constr. Facil.*, vol. 30, no. 3, p. 04015049, Jun. 2016, doi: 10.1061/(asce)cf.1943-5509.0000802.

[4] J. Seo, L. Duque, and J. P. Wacker, Field Application of UAS-Based Bridge Inspection, *Transp. Res. Rec.*, vol. 2672, no. 12, pp. 72–81, Dec. 2018, doi: 10.1177/0361198118780825.

[5] M. Rashidi, M. Mohammadi, S. S. Kivi, M. M. Abdolvand, L. Truong-Hong, and B. Samali, A decade of modern bridge monitoring using terrestrial laser scanning: Review and future directions, *Remote Sens.*, vol. 12, no. 22, pp. 1–34, 2020, doi: 10.3390/rs12223796.

[6] S. Feroz and S. A. Dabous, Uav-based remote sensing applications for bridge condition assessment, *Remote Sens.*, vol. 13, no. 9, 2021, doi: 10.3390/rs13091809.

[7] A. Hamdan *et al.*, Crack Width Detection for Concrete Structures Using Thermal Images and Artificial Neural Network, *Proc. - Int. Conf. Dev. eSystems Eng. DeSE*, pp. 19–24, 2024, doi: 10.1109/DeSE63988.2024.10911945.

[8] F. Hosny, S. Barakat, and S. A. Dabous, Statistical Analysis of Operational Carbon for Different Building Types in the UAE, *Jordan J. Civ. Eng.*, vol. 18, no. 2, pp. 346–359, 2024, doi: 10.14525/JJCE.v18i2.15.

[9] L. Duque, J. Seo, and J. Wacker, Bridge Deterioration Quantification Protocol Using UAV, *J. Bridg. Eng.*, vol. 23, no. 10, p. 04018080, Oct. 2018, doi: 10.1061/(asce)be.1943-5592.0001289.

[10] Y. F. Liu, X. Nie, J. S. Fan, and X. G. Liu, Image-based crack assessment of bridge piers using unmanned aerial vehicles and three-dimensional scene reconstruction, *Comput. Civ. Infrastruct. Eng.*, vol. 35, no. 5, pp. 511–529, May 2020, doi: 10.1111/mice.12501.

[11] R. Al-Ruzouq, S. Abu Dabous, M. T. Junaid, and F. Hosny, Nondestructive deformation measurements and crack assessment of concrete structure using close-range photogrammetry, *Results Eng.*, vol. 18, no. September 2022, p. 101058, 2023, doi: 10.1016/j.rineng.2023.101058.

[12] F. Jalinoos, M. Amjadian, A. K. Agrawal, C. Brooks, and D. Banach, Experimental Evaluation of Unmanned Aerial System for Measuring Bridge Movement, *J. Bridg. Eng.*, vol. 25, no. 1, p. 04019132, Oct. 2020, doi: 10.1061/(asce)be.1943-5592.0001508.

[13] S. Chen, D. F. Laefer, E. Mangina, S. M. I. Zolanvari, and J. Byrne, UAV Bridge Inspection through Evaluated 3D Reconstructions, *J. Bridg. Eng.*, vol. 24, no. 4, p. 05019001, Apr. 2019, doi: 10.1061/(asce)be.1943-5592.0001343.

[14] S. Dorafshan, R. J. Thomas, and M. Maguire, Benchmarking image processing algorithms for unmanned aerial system-assisted crack detection in concrete structures, *Infrastructures*, vol. 4, no. 2, Apr. 2019, doi: 10.3390/infrastructures4020019.

[15] S. Yoon, G. H. Gwon, J. H. Lee, and H. J. Jung, Three-dimensional image coordinate-based missing region of interest area detection and damage localization for bridge visual inspection using unmanned aerial vehicles, *Struct. Heal. Monit.*, vol. 20, no. 4, pp. 1462–1475, Jul. 2021, doi: 10.1177/1475921720918675.

[16] S. Abu Dabous and S. Feroz, Condition monitoring of bridges with non-contact testing technologies, *Autom. Constr.*, vol. 116, no. April, p. 103224, 2020, doi: 10.1016/j.autcon.2020.103224.

[17] G. Morgenthal *et al.*, Framework for automated UAS-based structural condition assessment of bridges, *Autom. Constr.*, vol. 97, pp. 77–95, Jan. 2019, doi: 10.1016/j.autcon.2018.10.006.

[18] F. Nex and F. Remondino, UAV for 3D mapping applications: A review, Nov. 08, 2014, *Springer*. doi: 10.1007/s12518-013-0120-x.

[19] Federal Highway Administration's (FHWA) Specifications, Bridge Inspector' s Reference Manual (BIRM), 2023.