Enhancing UAV Efficiency in Bridge Inspection through BIM-based Flight Planning and Image Quality Assurance

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Abstract –

Unmanned Aerial Vehicles (UAVs) have been widely applied for bridge inspection, and significant progress has been made to automate the UAV-enabled inspection process. However, current solutions face two primary challenges: (1) they typically rely on pilots' experience to create a pre-defined flight path for automated image collection, and (2) the potential for localisation errors and depth-varying bridge environments may lead to image quality issues such as blurriness, improper exposure, insufficient resolution, and coverage. To overcome these challenges, this paper introduces a novel framework that combines an objective Building Information Modelling (BIM)-based flight mission planning tool with an in-flight image-quality assessment module to ensure the comprehensive capture of high-quality images. A field experiment was carried out on a standard girder bridge to validate the effectiveness of this framework. The results show that the proposed framework: (1) can enable the collection of bridge images via a UAV with minor human intervention and (2) can ensure that the captured UAV images meet the inspection requirements, allowing for the reconstruction of a high-quality digital bridge model and effective detection and quantification of potential defects. The framework marks a pioneering approach for highly automated and efficient bridge inspection using UAVs and is versatile enough for application in diverse real-world bridge scenarios.

Keywords –

Bridge Inspection; Unmanned Aerial Vehicles (UAVs); High-quality Image Collection; Automation; BIM

1 Introduction

Bridges are a vital component of infrastructure systems, which require regular inspections to identify potential defects and provide maintenance recommendations [1,2]. In recent years, camera-mounted UAVs have become increasingly popular for bridge visual inspections, potentially replacing the traditional inspection equipment (e.g., rigging, scaffoldings, or heavy bucket trucks) and offering a safer, more cost-effective, and more efficient solution for bridge condition assessment [3].

After years of development, substantial progress has been achieved in UAV-enabled bridge inspection (UBI). Despite efforts made in this field, some aspects remain unaddressed. While current studies predominantly emphasise the automation of image collection, the planning process still relies on human experience, lacking a principled or automated tool for objective image capture plans [4,5]. Furthermore, the quality of images is challenging to predict, as it is influenced by unforeseen factors and can be easily affected by the bridge environment, such as uneven light conditions and varying depth [6,7].

This paper presents a systematic framework designed to automate the image collection process for UBI, which is expected to capture high-quality images sufficient for identifying potential defects and generating a photogrammetric 3D model at a metric scale. The proposed framework employs a BIM model of the target bridge and consists of two stages for achieving high-quality and efficient image acquisition.

The remaining part of this paper is structured as follows. Section 2 provides a comprehensive review of the development of UBI with a particular focus on the image collection process. In Section 3, the details of the proposed method are introduced. Section 4 describes a field experiment to validate the proposed framework. Section 5 discusses the applicability of this framework and suggests future research directions. Finally, we conclude this paper in Section 6.

2 Literature Review

This section begins with an overview of UAV-enabled bridge inspection. It then delves into a detailed analysis of the image collection process, with a particular emphasis on the level of automation (LoA).

2.1 UAV-enabled Bridge Inspection

Over the past few years, UAVs have attracted increasing interest in bridge inspection and made substantial advancements in this field. One of the representative studies was conducted by Seo, et al. [8], who evaluated the efficacy of camera-mounted UAVs as a novel tool for bridge inspection. This study successfully validated the effectiveness of UAV imagery for damage identification and demonstrated that UAVs can perform bridge inspection at a significantly reduced cost compared to conventional methods. Furthermore, Morgenthal, et al. [9] introduced a complete and coherent framework for UAV-based inspections of large bridges to support bridge condition assessment and data management. This framework stands as the pioneering guide for the UBI, encompassing the entire process from image collection and processing to management.

Many research interests have also been paid to investigate the performance of other types of UAV-mounted remote sensing systems in bridge inspection, including thermal cameras [10] and Light Detection and Ranging (LiDAR) sensors [11,12]. For example, Omar and Nehdi [10] utilised UAV infrared thermography to detect subsurface anomalies in concrete bridge decks. Bolourian and Hammad [11] employed a LiDAR-equipped UAV and proposed a 3D path planning method for automatically collecting precise point cloud data of bridges. Among the above-mentioned sensors, visual cameras are recognised as the most cost-effective and widely-used tool for UBI, particularly due to their outstanding performance in detecting various defects and considering the constraints of UAV onboard weight, power, and computing capabilities [7].

Existing studies on bridge inspection using a camera-mounted UAV can be classified into two approaches in terms of how the images are processed. The first approach is 2D image-based damage identification, which is to directly identify the defects from 2D images captured by the UAV using various image processing techniques such as edge detection methods [13], object-based analysis [14], and/or deep learning methods [15]. Through these methods, defects can be detected automatically, and their specifications can also be quantified via these image processing algorithms. Recent studies [16,17] have focused on investigating lightweight algorithms for the real-time detection and quantification of multiple-type defects at the same time.

The other approach is 3D model-based damage identification, which involves first reconstructing a photogrammetric 3D bridge model from the collected overlapping 2D images and then identifying and mapping the identified defects onto the 3D model, as demonstrated in various studies [5,18,19]. The 3D model-based damage identification is not only beneficial for providing superior 3D models with the accuracy to resolve defects but also can improve the interpretive capabilities and support the needs of infrastructure inspection [18].

2.2 UAV Image Collection

Image collection is one of the most critical processes in UBI, as the quality of the images directly affects the accuracy and effectiveness of bridge condition assessment. In this section, a specific review was conducted to evaluate the image collection in current UBI practice, with a particular emphasis on LoA. Referring to the criteria established in the field of autonomous cars [20], we classified the LoA of UAV-enabled bridge image collection into five levels: L1-Manual, L2-Partial Automation, L3-Conditional Automation, L4-High Automation, and L5-Full Automation.

Most of the studies [5,8,18] were identified to be at the lowest level of automation, i.e., L1. At this level, UAV pilots should be present and manually control the UAV all the time to capture the desired images at pre-determined areas of interest. The UAV is featured with a multi-directional obstacle awareness and emergency braking system, enabling it to automatically stop immediately in case of an emergency. A significant drawback of manual image collection is that the image collection process relies on pilots' experience, making the process time-consuming and susceptible to pilots' subjective errors.

To address the above issues, a feasible solution is to automate the image collection at a series of pre-determined viewpoints. Several studies [4,21] utilised the waypoint flight mission of the UAV to automatically capture images at a sequence of pre-defined waypoints for image collection. However, this automation depends heavily on precise UAV localisation throughout the flight. Most commercial UAVs (e.g., ©DJI, ©Skydio) support Global Positioning System (GPS)-based waypoint flight missions for automatic image collection for bridges. For partial critical inspection areas such as underneath bridge girders, the UAV must be manually operated to capture images due to the loss of GPS signals. Consequently, studies [4,21] employing GPS-based automated navigation are classified as L2 in terms of automation.

To facilitate automated image collection across the entire bridge environment, recent studies have proposed novel UAV localisation methods for estimating UAV's global pose in GPS-denied bridge areas, such as ultra-wideband (UWB) beacon-based [22] or fiducial marker-corrected stereo visual-inertial [23] localisation methods. With accurate global pose, these UAVs can autonomously navigate a pre-defined flight path covering the entire bridge environment. As such studies rely on a pre-existing environmental model to plan a pre-defined flight path, they fall into conditional automation, i.e., L3.

This level represents the most advanced automation achieved to date in UAV-enabled bridge inspection.

While recent technological advancements have significantly enhanced the utilisation of UAVs for automated image collection in bridge environments, existing methodologies, as highlighted in various studies [15,22,24,25], still grapple with some limitations. Primarily, these studies necessitate a pre-defined flight path, which is determined based on pilots' or inspectors' experience. Additionally, persistent challenges in image quality, encompassing issues like out-of-focus blurriness, improper exposure, and insufficient resolution and coverage, persist due to inherent errors in UAV localisation and the intricate nature of bridge environments, including uneven lighting conditions and UAV vibrations. These kinds of quality issues can significantly affect the performance of post-damage detection and quantification from images.

Table 1. LoA assessment of image collection process in UAV-enabled bridge inspection

References	LoA	Specifications	Limitations
[5,8,18]	L1	• Pilots manually operate the UAV to capture desired images all the time. • UAVs are featured an emergency braking system for added safety.	• Subjective error by UAV pilots. • Time consuming.
[4,21]	L2	• Requires a pre-defined obstacle-free flight path. • Automatic image collection is only achieved in GPS-available bridge areas.	• Significant human intervention is required for image collection in GPS-denied bridge areas.
[15,22,24,25]	L3	• Requires a pre-defined obstacle-free flight path. • The UAV should be capable of locating itself in the entire bridge environment.	• Human intervention is required in preparing the flight path for complex bridge structure. • Image quality issues exist.

3 Methodology

To address the identified gaps, this paper aims to propose a comprehensive framework for automated high-quality image collection, as presented in Figure 1. This framework employs a BIM model as input and comprises two primary stages: Preparation and Image Collection. Different from existing semi-automated [21] or automated image collection methods [25], this proposed framework incorporates several key features: (1) An objective and automated flight path planning algorithm to generate a flight mission based on inspection requirements for guiding the image capture of all target bridge areas; (2) An in-flight image quality check (IIQC) algorithm to rapidly assess the quality of UAV-captured images and to display the results with a multi-level colour-rendering system; (3) A supplemental image collection (SIC) step to ensure full coverage of the entire bridge with high-resolution UAV images. Detailed explanations of all components are described below.

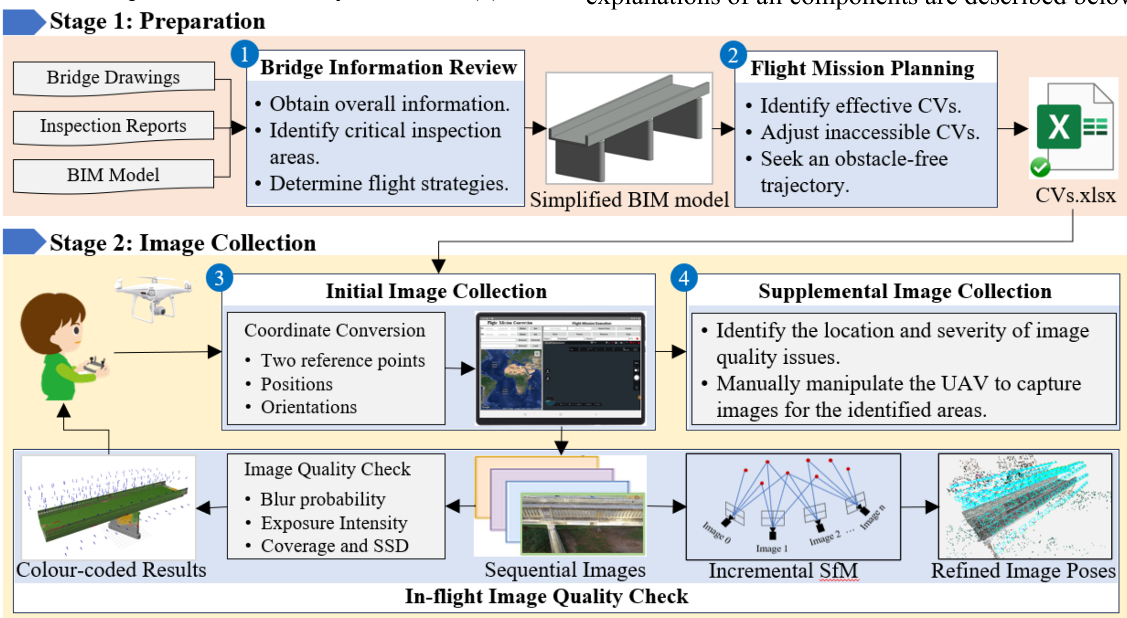

Figure 1. Overall framework for automated high-quality image collection in UAV-enabled bridge inspection

3.1 Preparation

The Preparation stage is essential for successful image collection using UAVs. It involves two key steps: Bridge Information Review and Waypoint Flight Mission Planning.

3.1.1 Bridge Information Review

Following the recommendation in [8], our framework starts with the Bridge Information Review step. This includes examining as-built plans, previous inspection reports, and other relevant documents to guarantee a comprehensive understanding of the target bridge. For example, the review of previous inspection reports can help inspectors identify critical inspection areas before planning the image capture plan, such as the bottom surfaces of girders and pier caps. The information gained during this step allows the pilot to develop reasonable flight strategies in bridge areas with limited accessibility, identify previous defects, and monitor or update critical damage, such as concrete cracks on the target bridge.

3.1.2 Flight Mission Planning

The Flight Mission Planning step is designed to identify a sequence of effective camera viewpoints (CVs) containing positions and orientations and seek an obstacle-free flight path through all the identified viewpoints. In our framework, an automated 3D flight mission planning tool (i.e., a Revit Plug-in), developed in our previous study [4], is employed to generate a waypoint flight mission based on a simplified BIM model of the bridge. Specific steps include (1) planning effective CVs for scanning each bridge part with sufficient resolution under photogrammetry constraints; (2) adjusting those inaccessible CVs due to UAV safety considerations and seeking alternative CVs that can achieve as much effectiveness as the original ones; (3) finding an obstacle-free trajectory through all the identified viewpoints. Figure 2 showcases the developed flight mission planning tool, which has been successfully validated on a range of bridge structures with varying shapes and sizes, as evidenced in the study [4].

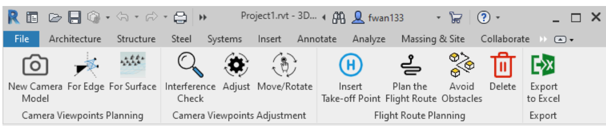

Figure 2. Developed Revit Plug-in for automated fight mission planning

3.2 Image Collection

Once the flight mission is created, in-field image collection can commence. This stage initially involves the UAV automatically executing the waypoint flight mission to collect desired images at those pre-defined viewpoints. This is followed by supplemental image collection (SIC) for areas not adequately captured in the initial step, conducted manually by the pilot. To offer effective guidance to the pilot, an in-flight image quality check module runs throughout this stage to rapidly assess the quality of UAV-captured images and display the results.

3.2.1 Initial Image Collection

Many UAV systems, such as DJI, Skydio, or those using the Pixhawk flight controller, feature an intelligent flight mode, enabling them to execute waypoint flight missions to fly to designated waypoints automatically and capture images. However, these systems rely heavily on GPS localisation data, and current drone mapping software (e.g., DJI Pilot, DroneDeploy, Pix4Dcapture) does not allow for the execution of custom waypoint flight missions. Therefore, we developed an Android app utilising the DJI Software Development Kit (SDK), as shown in Figure 3, to facilitate automated image collection in bridge areas where GPS signals are reliable. For autonomous flight in GPS-denied areas beneath bridge girders, existing commercial UAVs prove inadequate. Our previous study [23] introduced a custom-built UAV capable of accurately estimating its position in both GPS-available and GPS-denied bridge areas. Such a UAV is essential for automatically capturing all desired images according to a pre-generated waypoint flight mission.

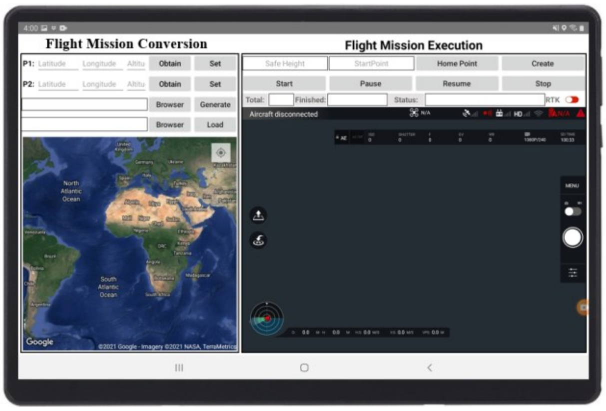

Figure 3. Developed Android App for automated image collection using DJI UAVs

3.2.2 In-flight Image Quality Check

Although the Initial Image Collection step achieves autonomous image capture, navigating a UAV accurately to pre-determined viewpoints remains challenging due to localisation and control errors. These difficulties can lead to images with insufficient resolution and coverage. Furthermore, bridge images captured by UAVs often suffer from other quality issues like blurriness and improper exposure, exacerbated by uneven lighting conditions and UAV vibrations. These issues can significantly hinder damage detection from images and bridge condition assessment. To tackle these problems and enhance image quality, we incorporate an image check module, named IIQC, into our framework, aiming at rapidly assessing the quality of UAV-captured images against the inspection requirements and providing immediate feedback to the UAV pilot, thereby guiding the collection of supplementary images.

The IIQC module utilises the BIM model as a reference to support image quality assessment and encompasses three key modules: (1) a coarse-to-fine image pose estimation module for obtaining precise image poses relative to the reference bridge model, (2) an image quality assessment module for comprehensively evaluating image quality in terms of blurriness, exposure, coverage, and surface sampling distance (SSD) at the pixel level. Figure 4 presents the pipeline of the image quality check and multi-level colour rendering system.

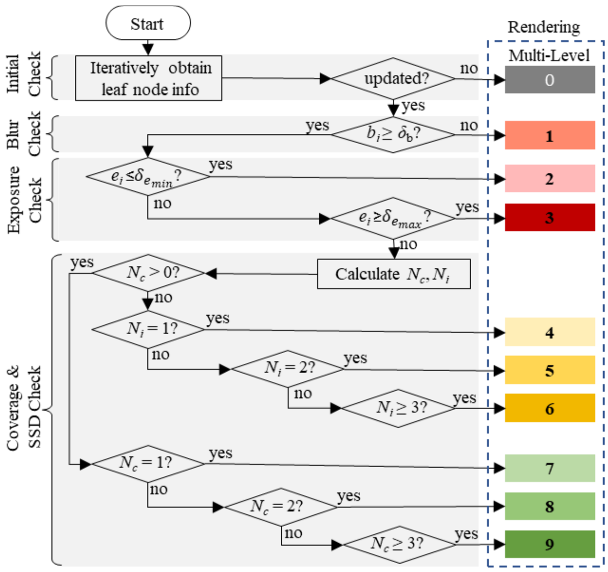

Figure 4. Pipeline of the in-flight image quality check and rendering system

3.2.3 Supplemental Image Collection

The colour-coded results from the IIQC allow the UAV pilot to effortlessly identify the location and severity of issues. Table 2 illustrates the recommended actions for different levels of evaluation results. With these guidelines, the UAV pilot can adeptly operate the UAV to specific areas for the re-collection of images. These newly captured images are then further evaluated and correlated with previous ones. This step stops until the target bridge is well captured. Finally, all images will be processed using commercial photogrammetry software (i.e., iTwin Captrue Modeler) to create a complete 3D digital model of the bridge and further processed to identify and quantify potential defects.

Table 2. Recommended actions for supplemental image collection

Level & Status		Recommended Actions
0	Missing areas	• Check the image capture plan and analyse the reasons. • Capture necessary images.
1	Blurry areas	• Recapture this area and keep an eye on the vibrations of the UAV.
2	Underexposure	• Check illumination condition. • Recapture this area.
3	Overexposure	• Adjust capture orientation to avoid areas that are too bright. • Recapture this area.
4	One insufficient capture	• Fly closer to the target surface. • Capture more images of this area.
5	Two insufficient captures	• Fly closer to the target surface. • Capture more images of this area.
6	Over three insufficient captures	• Fly closer to the target surface. • Recapture images of this area.
7	One valid capture	• Capture two more images of this area.
8	Two valid captures	• Capture one more image of this area.
9	Over three valid captures	• No further actions.

4 Experiment and Results

In this part, a field experiment was conducted to validate the feasibility of the proposed method.

4.1 Experimental Setup

The target bridge for testing is a typical girder bridge located in New Zealand, as shown in Figure 5. The UAV used in this experiment is DJI Phantom 4 Pro v2.0, equipped with a 20-megapixel sensor with the image resolution of 5472 × 3648 pixels. Since the bridge includes several similar spans, we only selected the middle area of the superstructure to validate the feasibility of the proposed framework.

Figure 5. Target bridge environment

4.2 Experimental Results

This experiment strictly follows the workflow in the proposed framework. Figure 6 illustrates the results of each step. Firstly, critical information regarding the target bridge, such as the 2D drawings and historical inspection reports, was reviewed. According to the drawings, a 3D BIM model of the bridge was created. Secondly, a waypoint flight mission was created to scan the tested areas using the developed Revit Plug-in. The expected spatial resolution was set to 1.5 mm/pixel with an overlap of 66.7%, as suggested by [26]. Subsequently, we moved to on-site image collection. The developed Android app was utilised to facilitate the UAV to automatically captured the expected images within the generated flight mission, with 365 images being automatically captured with a time cost of 55 minutes. Meanwhile, the IIQC module ran on a standard laptop and provided image quality metrics results in near real-time. Finally, according to the colour-coded results, the UAV pilot controlled the UAV to capture more images to ensure all areas of interest were well captured by high-quality images. Finally, a total of 510 images were captured. The results show that the proposed framework is feasible for practical bridge image collection.

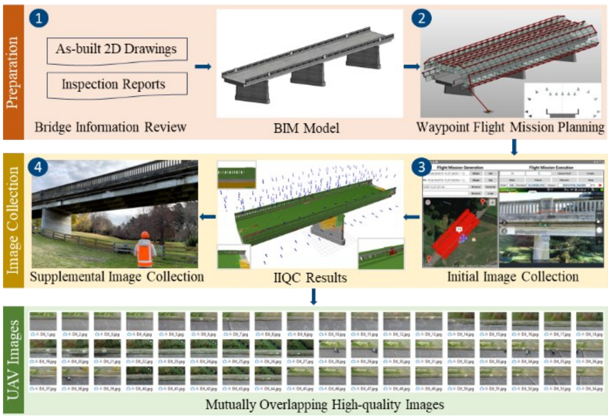

Figure 6. Results of the collected images using the proposed framework

To further evaluate the effectiveness of the newly involved IIQC module, we further processed the captured images using commercial photogrammetry software, i.e., iTwin Capture Modeler, to generate a 3D digital model. We compared the quality of the reconstructed models using only the images captured during the initial image collection and all images, including the supplemental images. The example outcomes of the comparative experiment are depicted in Figure 7. The findings from this experiment validate the value of the SIC step, which involves capturing supplementary images in areas that may not have been adequately covered during the initial image collection and ensuring the reconstructed model with high quality to identify and map the potential defects.

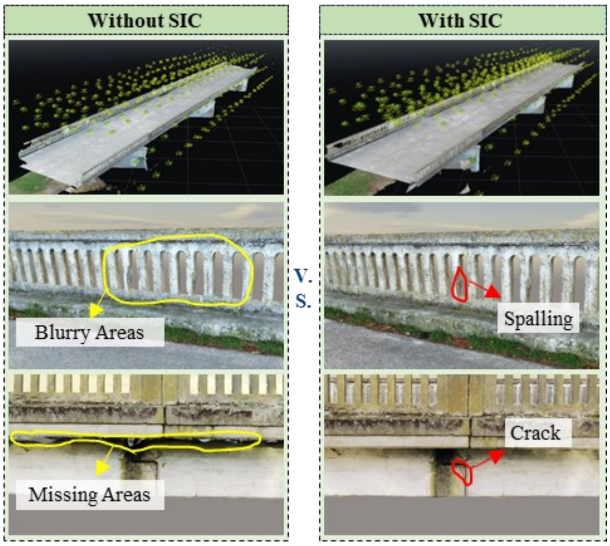

Figure 7. Comparison between the pre-supplemental collection and post-supplemental collection

5 Discussion

This paper introduces a BIM-supported framework for automated, high-quality image collection using a UAV. By integrating automated flight mission planning, automated image collection, an in-flight image quality check module, and supplemental image collection, the framework enables UAVs to capture high-quality images for bridge inspections with minimal human intervention. The proposed framework is versatile and can be readily applied to most bridge structures that have clear surroundings.

While the framework shows promising results, it still has limitations. It operates under the assumption of a clear bridge environment or that surrounding obstacles are pre-modelled for flight mission planning. In complex bridge environments with trees or power lines, significant human input is still necessary. Additionally, the framework depends on a pre-existing bridge model for flight path planning and in-flight image quality check, which poses a challenge for ancient bridges. In the future, UAV-enabled image acquisition for bridge inspection is anticipated to progress towards full autonomy, eliminating the need for a pre-determined flight path and reliance on a bridge model as prior knowledge, as shown in Figure 8.

To achieve the level of high automation, the UAV will be enabled with real-time environment sensing and adaptive path replanning capabilities by integrating advanced SLAM algorithms like RTAB-MAP [27] and deep reinforcement learning-based path planning algorithms [28]. Regarding the ultimate goal of full automation, research can focus on enhancing the UAV's capability for semantic environmental modelling by integrating advanced image-based [29] or point cloud-based [30] semantic segmentation algorithms. In this stage, UAVs will be able to autonomously execute inspection tasks without any human intervention during flight, making them suitable for rapid post-disaster bridge condition assessments.

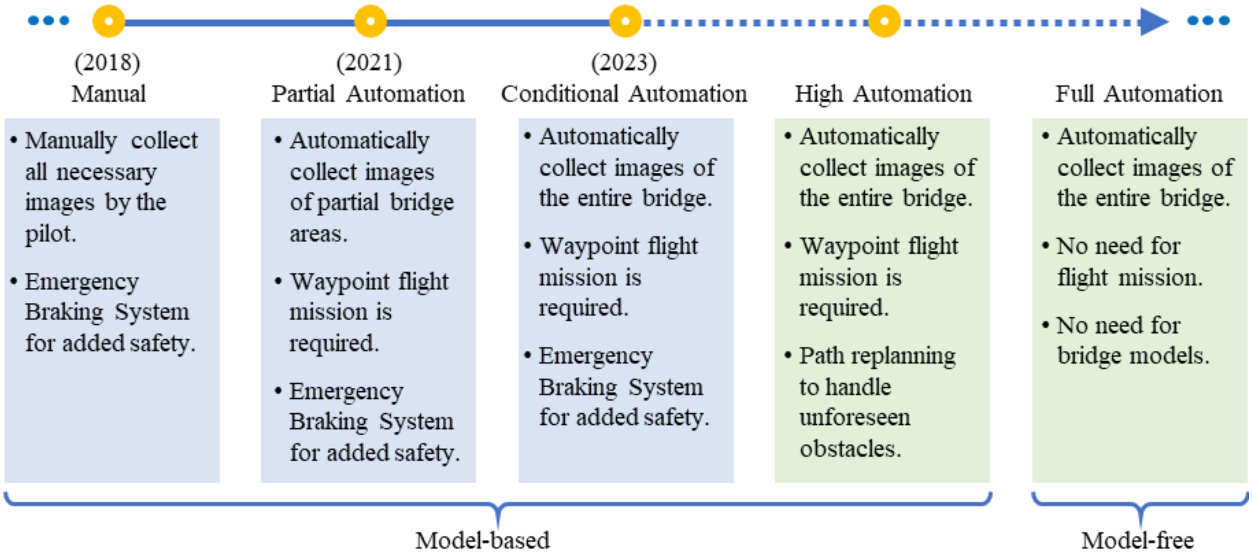

Figure 8. A vision of automated UAV image collection for bridge inspection

6 Conclusions

This paper presents a holistic framework for automated UAV image collection for bridge inspection by incorporating a set of tools to enable high automation and ensure the collection of high-quality images. The feasibility of the framework has been validated through a field experiment, leading to the following conclusions:

1. The tools incorporated within this framework can significantly diminish the necessity for human intervention and streamline all sequences of UAV-enabled bridge image collection, from the initial preparation to on-site image collection.
2. The IIQC module, coupled with the supplemental image collection within this framework, can guarantee that the UAV-captured images are of high quality for reconstructing a 3D digital model of the bridge and for the effective identification and quantification of potential defects.

The main contributions of this paper are listed below:

1. A systematic framework has been proposed for fully automated high-quality image collection for bridge inspection using UAVs and BIM (Figure 1).
2. All algorithms and tools developed to enhance UAV efficiency in bridge inspection have been made available as open-source resources (Github).
3. A vision towards fully autonomous UAV image collection for bridge inspection has been presented, charting a direction for future research (Figure 8).

Code Availability

The Revit Plug-in for automated path planning is available at https://github.com/fwan133/MissionPlanner.

The Android App for automated image collection is available at https://github.com/fwan133/DJI_App.

The IIQC project for rapid image quality check is available at https://github.com/fwan133/IIQC.

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