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Autonomous Drone Prototype for Bridge Inspection and Maintenance

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1 Introduction

1.1 BACKGROUND AND MOTIVATION

Bridges are critical components of California’s transportation infrastructure, with over 26,000 structures requiring regular inspection to ensure public safety. The California Department of Transportation (Caltrans) Structure Maintenance and Investigation (SM&I) division is responsible for managing and inspecting these in-service state and locally owned bridges.

Traditional inspection methods are often time-consuming, costly, and pose safety risks to personnel. Drones have emerged as a promising technology to enhance the efficiency, accuracy, and safety of bridge inspections. However, current drone-based approaches are still heavily reliant on manual piloting and are often not optimized for the specific requirements of structural condition assessment. The integration of autonomy into drone inspection workflows has the potential to address these limitations and better align with Caltrans’ operational needs.

This final report summarizes the design, development, and initial testing of an autonomous drone-based bridge inspection system. Building on earlier tasks, including a literature review of drone technologies, identification of regulatory and operational constraints, and the development of a working drone prototype, this report presents the proposed inspection workflow, details of each component, and shares results from flight experiments, as well as findings and recommendations for future work.

1.2 INDUSTRY SURVEY AND EXISTING SOLUTIONS

The use of drones for infrastructure inspection has gained significant attention in recent years due to their potential to improve inspection efficiency and safety. Several commercial solutions, such as those offered by DJI and Skydio, provide drone platforms capable of semi-autonomous or autonomous flight and data capture.

Current autonomous drone solutions from companies such as DJI and Skydio generally require operators to predefine flight waypoints on a GPS map. These waypoints and camera angles are often fine-tuned through trial and error to capture the desired images, making the process time-consuming and inflexible, particularly when multiple viewing angles are necessary.

An alternative “two pass” approach involves an initial flight to explore the environment and generate a rough model or map, followed by a second pass to perform a uniform, high-resolution

scan for model refinement. While this method can be effective in some contexts, it might not be efficient for bridge inspections, where only specific components need targeted high-resolution imaging.

1.3 BRIDGE INSPECTION REQUIREMENTS AND OBSERVATIONS

Bridge inspections involve assessing the condition of various structural components to ensure safety and integrity. Manual inspections, traditionally conducted by trained engineers, focus on identifying defects such as cracks, corrosion, spalling, and other signs of deterioration. These inspections rely heavily on visual observations and require capturing detailed imagery for accurate assessment.

A critical requirement for effective bridge inspection is image resolution. For example, cracks wider than 0.05 inches are typically considered indicators of poor condition in reinforced concrete girders or beams. To detect such defects, the drone's imaging system must be capable of capturing high-resolution images with sufficient clarity, which depends on the drone's distance from the inspected surface.

Bridge inspections require component-specific imaging criteria. Different bridge elements demand varying levels of detail to effectively identify relevant defects. Applying a uniform image resolution across the entire bridge can lead to inefficiencies in both data collection and analysis. For example, small cracks on the bridge deck may be less critical than similar cracks on a bridge pier. Therefore, coarser image resolution may be acceptable for inspecting the deck, while higher resolution is necessary for critical components like piers.

Additionally, bridge inspectors often have access to prior information such as as-built drawings, CAD models, and historical inspection data. This prior knowledge can guide drone inspection missions to focus on critical areas and optimize flight paths and imaging strategies.

Based on these inspection requirements and industry insights, the next section details the methodology for designing and implementing the autonomous drone-based bridge inspection system. This includes the system architecture, hardware selection, flight workflow, and key assumptions made during development and testing.

2 Methodology

Figure 2.1 illustrates the proposed autonomous drone-based bridge inspection workflow. The system is structured into two main phases: **offline planning and processing** and **onboard autonomous execution**.

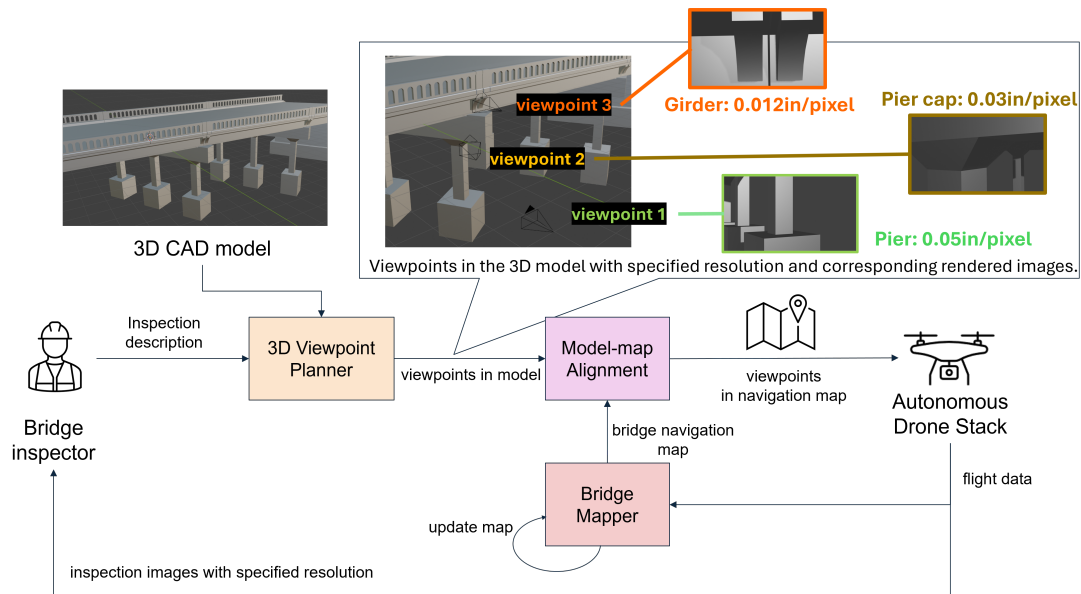


Figure 2.1: Autonomous drone-based bridge inspection workflow

2.1 OFFLINE PLANNING AND PROCESSING

The offline phase prepares all necessary data and coordinates for the drone to operate autonomously, particularly in GPS-denied environments. This phase includes three key modules:

- **3D Viewpoint Planner:** Engineers utilize prior knowledge and 3D CAD models of the bridge to define precise inspection viewpoints. Using a custom interface built in Blender, inspectors position virtual cameras to simulate drone perspectives and preview expected imagery. This approach allows efficient planning of viewpoints with the required image resolution tailored to critical bridge components.

- **Bridge Mapper:** Since drones rely on sensor data for localization and navigation, a navigation map is constructed using Simultaneous Localization and Mapping (SLAM) during an initial exploratory phase. This process is implemented via the RTAB-Map package (Labbé and Michaud, 2019) within the drone’s software stack. The resulting dense point cloud map captures the static bridge environment and is reused in subsequent missions, reducing the need for remapping. Various mapping strategies can be employed. For example, manually piloting the drone while running SLAM, or using more advanced, autonomous exploration algorithms such as next-best-view (NBV) planning. For simplicity in the following experiment, the drone was carried by hand around the structure while recording stereo camera data, which was then used to generate the navigation map required for the flight mission.
- **Model-Map Alignment:** To ensure consistency between the CAD model used for planning and the SLAM-generated navigation map, an alignment process is used to identify common reference points. This transforms inspection viewpoints from the CAD coordinate frame into the drone’s navigation frame for accurate mission execution. In the following experiment, this step was performed manually due to the complexity of the mesh model and limited computational resources. It was found that manual alignment was more practical and efficient in this context. However, automated alignment may be feasible when using lightweight digital models such as BIM.

2.2 ONBOARD AUTONOMOUS EXECUTION

Once the inspection viewpoints are transformed and uploaded, the drone autonomously performs the mission through the following capabilities:

- **Vision-Based State Estimation:** Using OpenVINS (Geneva et al., 2020), a visual-inertial odometry system, the drone estimates its position and orientation in real-time by fusing stereo camera images with inertial measurements, enabling stable flight without GPS.
- **Mapping and Localization:** RTAB-Map builds and maintains a 3D map of the environment to correct drift and enable relocalization during flight, anchoring the drone’s position to a consistent global reference frame.
- **Local Trajectory Planning:** The RAPPIDS planner (Bucki et al., 2020) generates collision-free trajectories at 30 Hz by partitioning the drone’s field of view and reacting dynamically to obstacles, ensuring safe navigation to each inspection viewpoint.
- **Flight Control:** Low-level rate controllers translate planned trajectories into motor commands via the autopilot and electronic speed controllers, achieving precise drone maneuvering.

2.3 DRONE HARDWARE AND SOFTWARE STACK

The drone prototype consists of three primary hardware components:

- **Depth Camera (Intel D455):** Provides stereo and depth images for state estimation and obstacle avoidance.
- **Onboard Computer (Qualcomm RB5):** Performs all high-level computations, including planning, control, and communication.
- **Autopilot (Pixracer) and ESC:** Executes low-level motor control commands for stable flight.

The integrated software stack combines OpenVINS, RTAB-Map, and RAPPIDS modules to enable SLAM-based mapping, GPS-denied localization, and real-time local collision avoidance, collectively supporting safe and autonomous inspection flights.

For a comprehensive technical description, please refer to Report 3, Sections 2 and 3.

2.4 FLIGHT TESTS

The following subsections describe three flight experiments conducted to validate the proposed inspection workflow and drone prototype. These include one indoor laboratory test and two outdoor real-world bridge inspections. The drone performed autonomous flight between inspection viewpoints, while a human operator was responsible only for initiating takeoff and landing, triggering transitions to the next viewpoint, and issuing emergency stop commands as safety measures. For the outdoor flight test, a GoPro 5 camera was attached to the drone to collect first-person-view (FPV) videos for documentation purposes.

2.4.1 Test 1: PEER Big Press Experiment

A flight test was conducted in an indoor environment at the PEER Big Press facility to validate the inspection workflow and drone autonomy (see Figure 2.2). Two primary models were constructed: a textured mesh model of the Big Press generated via photogrammetry using 3DF Zephyr, and a navigation map created by running RTAB-Map SLAM on the drone's onboard computer. Manual alignment was performed between the mesh and point cloud to ensure proper transformation from the mesh model coordinate to the navigation map coordinate.

Three inspection viewpoints were specified in Blender, carefully planned to include a potential collision risk between Viewpoints 1 and 2, thereby evaluating the local collision-avoidance planner (illustrated in Figure 2.3). The drone executed the mission fully autonomously under pilot supervision, successfully navigating the planned trajectory while capturing images. Quantitative analysis showed average position tracking errors between 0.08 m (3.15 in.) and 0.20 m (7.87 in.) and yaw errors below 2 degrees across viewpoints.



Figure 2.2: Big Press at PEER facility (originally presented in Task 3 report).

2.4.2 Test 2: Caltrans Bridge 1 (20 0019Y)

The first Caltrans bridge test targeted a 3-span reinforced concrete beam bridge (Figure 2.4). Similar to Test 1, aerial images collected by manual drone flight were processed via 3DF Zephyr to create a high-fidelity textured mesh model, and a navigation map was generated by carrying the drone around the bridge while collecting stereo data. Manual alignment was used to merge model and map frames.

Five inspection viewpoints covering critical bridge components were specified in the Blender interface (Figure 2.5). The drone performed the flight autonomously, completing all waypoints with operator control limited to takeoff and landing. Captured imagery allowed for structural condition assessment, revealing features such as efflorescence and corrosion.

2.4.3 Test 3: Caltrans Bridge 2 (33 0046Y)

The second Caltrans bridge test examined a steel truss bridge with challenging environmental factors, including vegetation movement and variable lighting (Figure 2.6). Photogrammetry reconstruction quality was lower compared to Bridge 1 due to these conditions. The navigation map was similarly created via RTAB-Map SLAM.

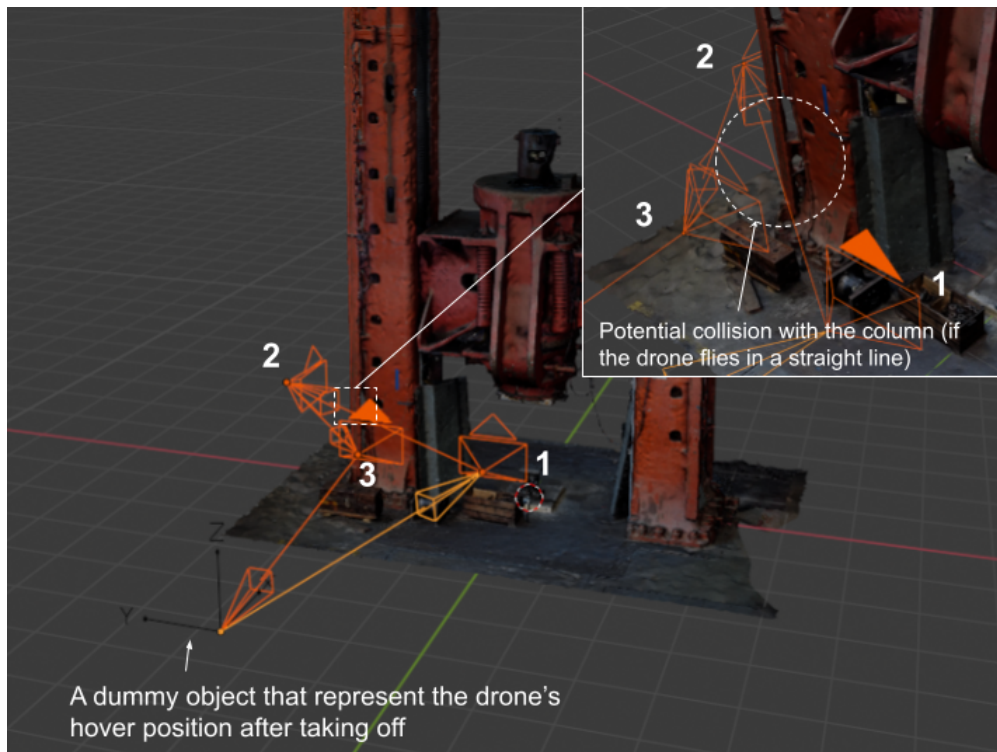


Figure 2.3: Planned viewpoints for the Big Press flight experiment (originally presented in Task 3 report).

Due to the vision-based state estimator drift under poor lighting and limited visual features, flight altitude was restricted to approximately 1.3 meters above the deck for safety. Five viewpoints, including roadway and truss structure views, were specified (Figure 2.7). Despite constraints, the drone successfully captured inspection images autonomously.



Figure 2.4: Overview of Bridge 1 (20 0019Y) (originally presented in the Task 1 and Task 4 reports).



Figure 2.5: Planned viewpoints for Bridge 1 (20 0019Y) flight experiment (originally presented in the Task 4 report).



Figure 2.6: Overview of Bridge 2 (33 0046Y) (originally presented in the Task 1 and Task 4 reports).

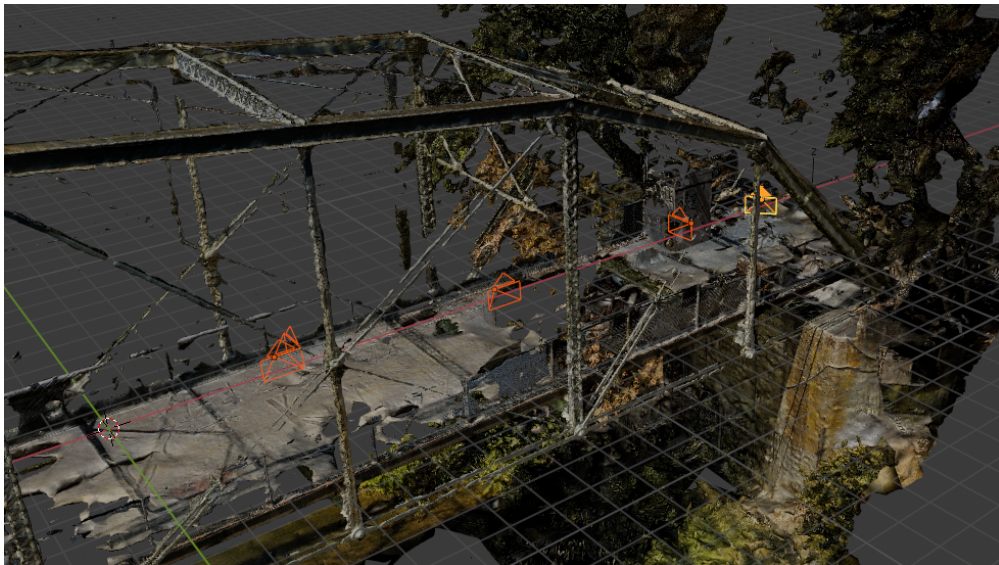


Figure 2.7: Planned viewpoints for Bridge 2 (33 0046Y) flight experiment (originally presented in the Task 4 report).

3 Results and Future Work

3.1 EXPERIMENTAL RESULTS

All three inspection plans were successfully executed. The drone was able to localize and navigate autonomously to the desired positions to capture images without relying on GPS, demonstrating effective obstacle avoidance capabilities. The experiment videos can be found in <https://berkeley.box.com/s/f9ge0m9lq5c16j4ze1j3vjkccft4ui4k> (Big Press), <https://berkeley.box.com/s/7iwcqt2lyphjhprajvt3y5b9lr755a7s> (Bridge 1, 20 0019Y) and <https://berkeley.box.com/s/dbvb4618o3y5puoqhye89hrxna2jh52d> (Bridge 2, 33 0046Y). These video recordings were originally presented in the Task 3 and Task 4 reports.

Figures 3.1, 3.2, and 3.3 show the inspection images captured by the drone, which are visually well-aligned. Several defects can be identified from these images. For example, rust and scratches on the Big Press machine; efflorescence on the girder of Bridge 1; and corrosion near the pier–bent cap joint of Bridge 1. Because Bridge 2 is a steel structure, structural defects such as cracks are less common. However, the images show no signs of bending or deformation in the steel components.

3.2 FINDINGS, RECOMMENDATIONS AND FUTURE WORK

Overall, the inspection system performed well, successfully executing autonomous navigation and image capture in both indoor and outdoor environments.

From the offline planning perspective, a key takeaway is the use of a mesh model due to the absence of Building Information Models (BIM) or CAD models. While the mesh provides a high-fidelity and visually detailed representation beneficial for inspection planning, it is computationally heavy and presents challenges in aligning with the point cloud data generated by RTAB-Map, which is used for navigation. In contrast, planning with a BIM model would simplify alignment, as BIM models embed structural component segmentation and enable the specification of inspection viewpoints tailored to each component’s required resolution according to inspection manuals. This capability can significantly streamline and improve the accuracy of mission planning.

Regarding the drone platform, two main challenges were observed during the flight experiments. First, wind disturbances affected flight stability and precise positioning, especially during outdoor inspections. Second, the non-uniform lighting conditions under the bridges, with dark



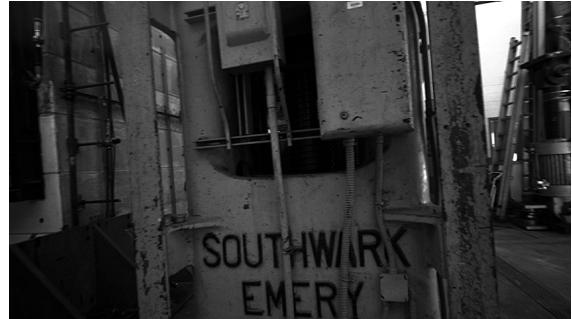
((a)) Viewpoint 1 rendered image.



((b)) Viewpoint 1 captured image.



((c)) Viewpoint 2 rendered image.



((d)) Viewpoint 2 captured image.



((e)) Viewpoint 3 rendered image.



((f)) Viewpoint 3 captured image.

Figure 3.1: Comparison of rendered and captured images.

shaded areas beneath and very bright exposure outside, negatively impacted the performance of vision-based sensors and the quality of captured images. Additionally, a lack of stable visual features, such as on the steel structure of Bridge 2, further complicated the performance of the pure vision-based localization and navigation algorithm used on the drone prototype.

To address these limitations, a more robust approach such as multi-sensor fusion is recommended. For example, integrating visual sensors with LiDAR and GPS could improve localization accuracy and system resilience under challenging lighting and texture-deficient conditions. This would enhance the reliability of autonomous navigation, especially in real-world inspection scenarios involving complex and variable environments.

Several areas have been identified for future development to improve the system's automation, robustness, and inspection efficiency:

1. **Integration with BIM Models:** Developing or integrating BIM into the planning workflow would enhance the offline planning phase. BIM enables semantic segmentation of structural components and provides geometric consistency, which can greatly improve alignment with navigation maps, support more structured planning, and potentially enable other model-based structural analyses.
2. **Autonomous Viewpoint Planning:** Implementing an advanced viewpoint planning algorithm that considers the inspection requirements of various bridge components (e.g., resolution, coverage angle, surface orientation) based on inspection guidelines could further automate mission setup and ensure comprehensive and targeted coverage.
3. **Multi-Sensor Fusion for Localization:** To overcome the limitations of vision-only localization under variable lighting and low-texture conditions, incorporating LiDAR and GPS into a multi-sensor fusion framework could significantly improve navigation accuracy and overall system robustness in complex or dynamic environments.
4. **Autonomous Defect Detection, Evaluation, and Localization on Digital Models:** A future system could integrate machine learning or computer vision techniques to automatically detect and assess structural defects (e.g., cracks, corrosion) from inspection images. These defects could then be localized within a BIM or digital model, associating them with specific structural elements. This would enable structured inspection reporting, facilitate historical tracking of damage progression, and support integration with digital asset management platforms.

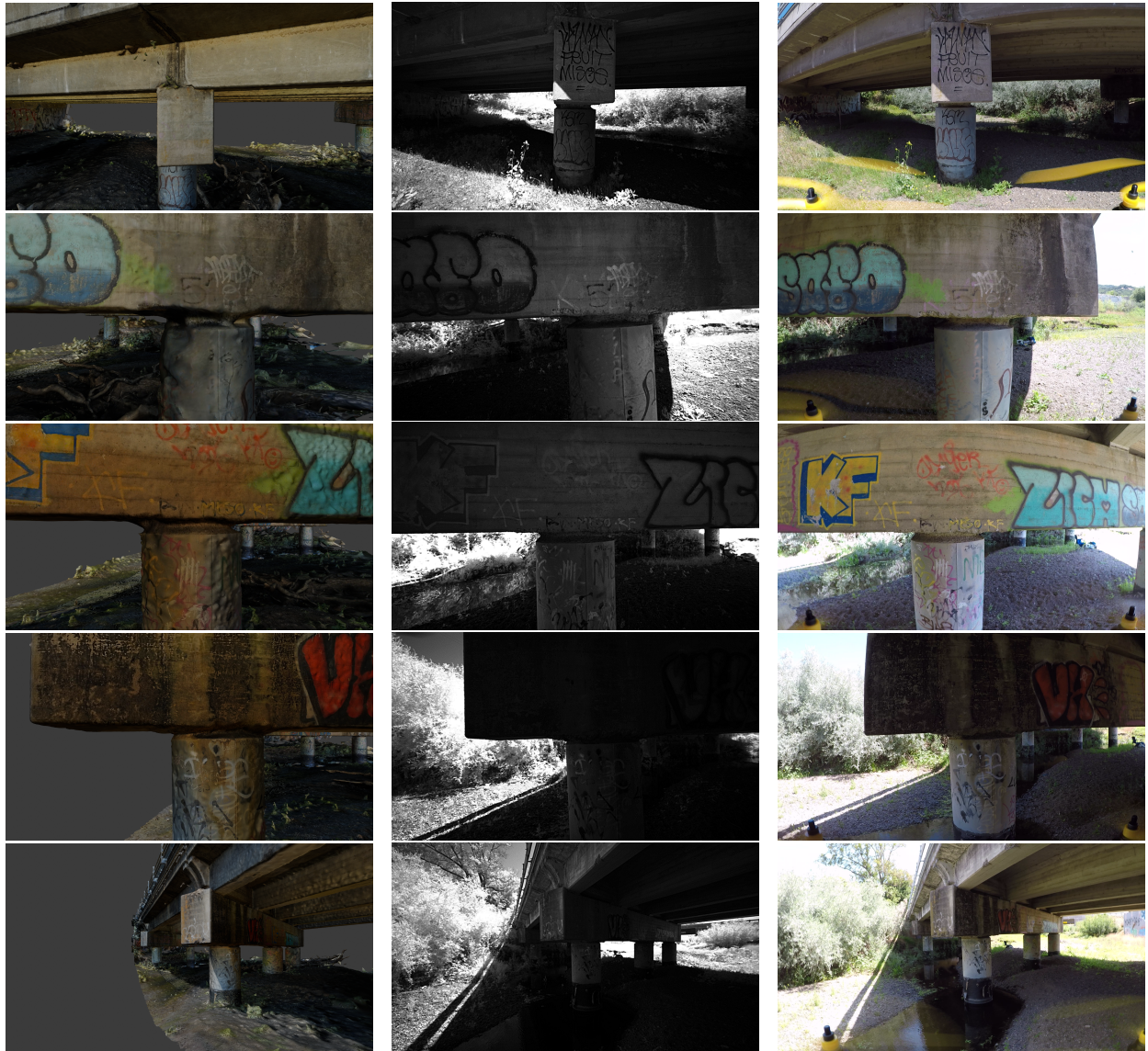


Figure 3.2: Comparison of rendered and captured images of bridge 1 (20 0019Y). Rows correspond to Viewpoints 1 through 5, from top to bottom. Left column: rendered images; middle column: images captured by the drone’s onboard camera (after white-balancing processing); right column: snapshots from the GoPro FPV video. Note: GoPro images appear distorted due to the wide-angle lens.

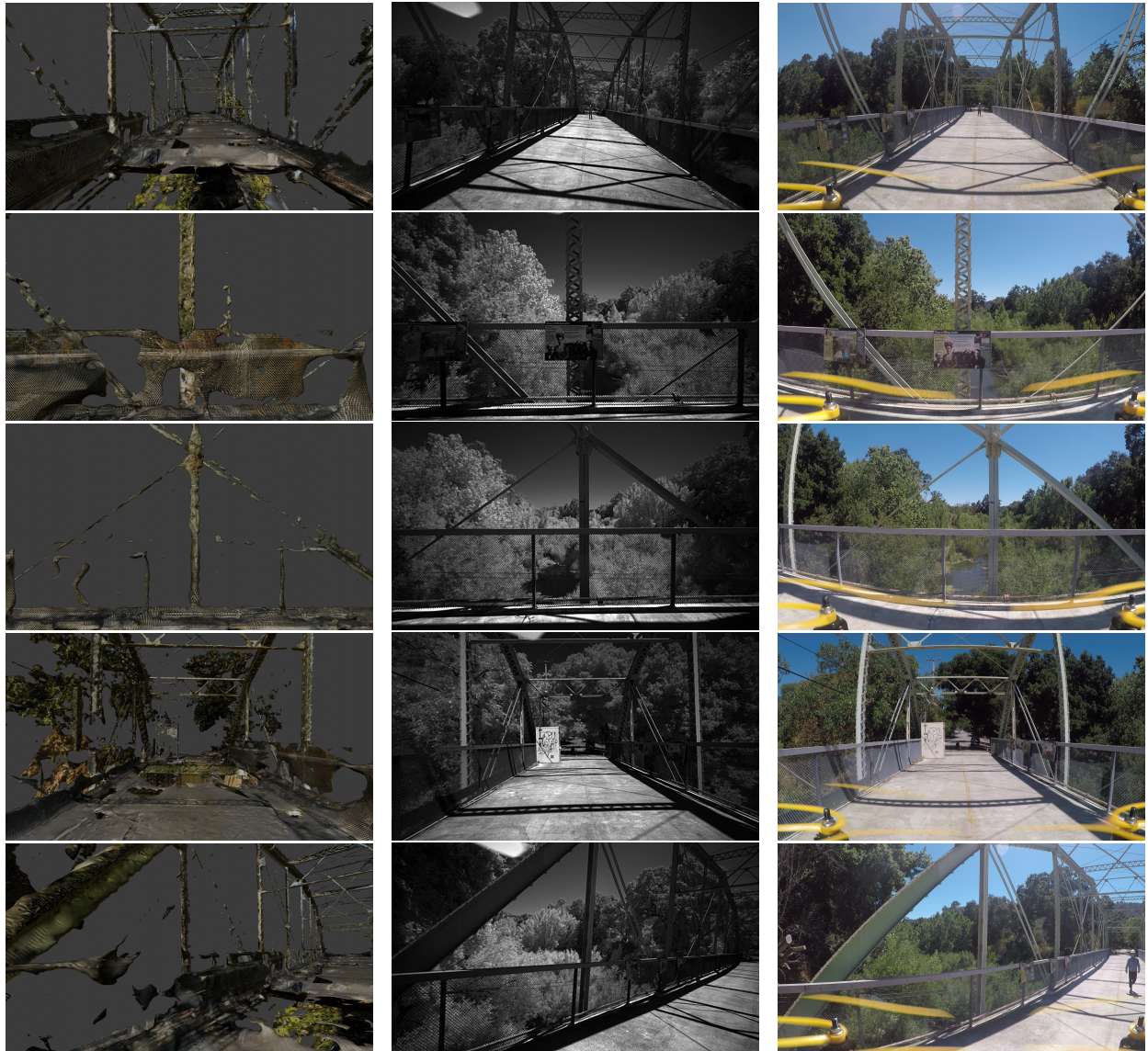


Figure 3.3: Comparison of rendered and captured images of bridge 2 (33 0046Y). Rows correspond to Viewpoints 1 through 5, from top to bottom. Left column: rendered images; middle column: images captured by the drone’s onboard camera (after white-balancing processing); right column: snapshots from the GoPro FPV video. Note: GoPro images appear distorted due to the wide-angle lens.

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