Monorail bridge inspection using digitally-twinned UAVs

Lanh V. Nguyen[1,*], *Trung H.* Le[1], *Thao D.* Nguyen[2], *Ngai M.* Kwok[3], and *Quang P.* Ha[1]

[1]School of Electrical and Data Engineering, University of Technology Sydney, Ultimo NSW 2007, Australia
[2]Vietnam Naval Academy, Nha Trang, Vietnam
[3]School of Engineering, Design and Built Environment, Western Sydney University, Penrith NSW 2751, Australia

Abstract. This paper introduces a comprehensive approach to monorail bridge inspection utilizing unmanned aerial vehicles (UAVs) and digital twin technology. The autonomous UAV-based inspection design encompasses UAV dynamics, tracking control, path planning, and task execution. A dedicated digital twin platform is developed to facilitate rigorous testing and verification of UAV control, mitigating the necessity for extensive physical testing. Methodology validation is achieved through a combination of simulations and real-world experiments, affirming its efficacy in authentic scenarios and demonstrating the potential for advancing infrastructure inspection practices.

Keywords: UAV; digital twins; smart inspections

1 Introduction

As the world pursues a more sustainable future, maintaining critical infrastructure like viaduct structures for motorways gains importance in minimizing environmental impact. Viaducts traverse ecologically sensitive areas, raising concerns about traditional testing methods reliant on heavy machinery and on-site presence, which can harm local ecosystems [1]. In response, our research employs camera-equipped unmanned aerial vehicles (UAVs) for precise and environmentally friendly inspections. Simultaneously, we develop dynamic digital twin technology, a virtual replication of monorail bridges and surroundings. This digital twin efficiently validates autonomous UAV-based inspections.

Our approach builds upon a foundation of related work in the fields of UAV technology, digital twins, and environmental sustainability [2–4]. Previous studies have demonstrated the promise of UAVs for bridge inspections, showcasing their ability to access challenging locations and capture high-resolution data without ecological disruption [5, 6]. Additionally, digital twin technology has gained attention across various domains, such as industrial robots and self-driving cars [7, 8], offering real-time monitoring, control, and decision-making capabilities.

Building on prior works in UAVs for bridge inspections and digital twin development, this research integrates these technologies into a comprehensive framework. We emphasize efficient validation of autonomous UAV-based inspections using emerging digital twin technology. These twins offer a controlled, highly realistic simulation, markedly reducing

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[*] Email: vanlanh.nguyen@uts.edu.au.

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the need for disruptive field testing. They facilitate data-driven maintenance aligned with environmental goals, cost-efficiency, and broader sustainability objectives.

In the following sections, we will highlight how the strategic combination of UAVs with digital twins enhances monorail bridge inspection capabilities, emphasizing the benefits it brings for both the environment and infrastructure.

2 UAV-based monorail bridge inspection

The UAV flight control technique for bridge inspection involves four key components: UAV dynamics, tracking control, path planning, and task execution (Figure 1). Path planning determines the optimal flight path, tracking control ensures precise path adherence, UAV dynamics model vehicle behaviors in the environment, and task execution considers all working conditions.

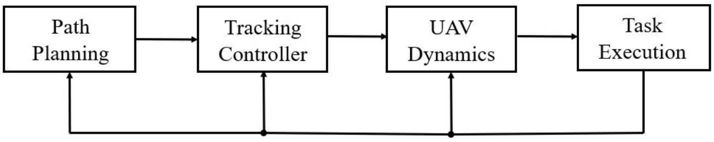


Figure 1. Structure of UAV-based inspection

2.1 UAV dynamics

Effectively controlling the UAV requires a comprehensive understanding of its dynamics. The quadcopter configuration (Figure 2) comprises four rotors and propellers generating thrust forces (F_i, $i = 1, 2, 3, 4$) at varying distances (l) from the center. UAV position is defined by the x, y, z axes, and orientation is determined by roll (ϕ), pitch (θ), and yaw (ψ) angles. Clockwise rotation of rotors 1 and 3, and counterclockwise rotation of 2 and 4 control yaw. Vertical motion adjusts with all rotor speeds; pitch is influenced by rotors 1 and 3, and roll by rotors 2 and 4. The dynamics of multirotor UAVs can be obtained generally via the Lagrangian formulation, from which a simplified quadcopter model is given in [9].

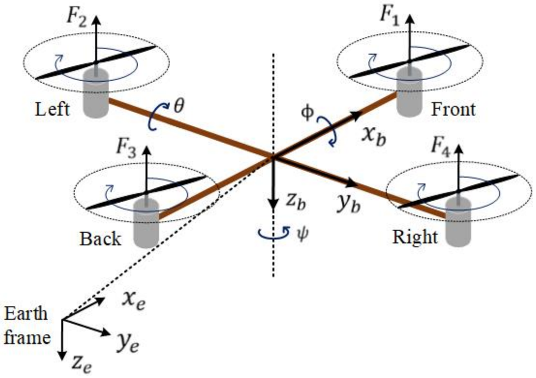


Figure 2. Configuration of the UAV [9]

2.2 Tracking controller

The tracking controller in an autonomous UAV dedicated to bridge inspection plays an important role in for ensuring precision, safety, and reliability during the inspection process.

It enables the UAV to navigate its environment effectively while capturing essential data for assessment and maintenance. A commonly employed approach for trajectory tracking control is a cascade control structure (Figure 3). This structure divides the control system into loops, with UAV control hierarchically organized for different degrees of freedom (DOF). The inner loop focuses on attitude control, ensuring stable flight and precise trajectory tracking. The outer loop manages position control, necessary for trajectory tracking and mission success. This division into separate loops within the hierarchical control scheme enhances UAV movement control efficiency, improving overall performance and reducing coupling between DOF. This reduction enhances control stability and accuracy, making the hierarchical control scheme indispensable for UAV control in inspection applications.

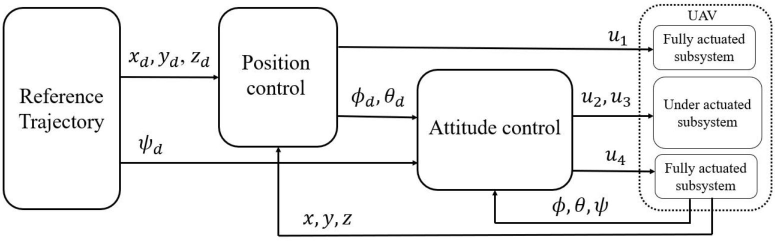


Figure 3. Control architecture of UAVs

2.3 Path planning

Path planning is essential to deploy UAVs for the tasks of bridge inspection, generating a safe, efficient trajectory. It considers factors like obstacle avoidance, energy efficiency, and dynamic adaptability, as well as constraints such as coverage area, traveling distance, threat avoidance, and turning angle limits. By addressing these, path planning becomes an optimization problem, minimizing a cost function for the UAV to ensure effective and precise inspection. It closely coordinates with the tracking controller for safe task execution. Our approach formulates path planning as an optimization problem by incorporating constraints into a cost function. The multi-objective cost function for the UAV is expressed as:

$$J(\mathcal{P}) = \omega_3 F_{tr} + \omega_2 F_{sa} + \omega_3 F_{sm} + \omega_1 F_{co}, \tag{1}$$

where $\mathcal{P}$ is the UAV path and ω_i for $i = 1, 2, ..., 4$ are weight coefficients. The traveling distance cost F_{tr}, the safety cost F_{sa}, and the smoothness cost F_{sm} can be found in [10]. Here, the coverage-related cost F_{co} is defined as:

$$F_{co} = \sum_{k=1}^{K} [H_b(k) - H_c(k)] + \beta \sum_{k=1}^{K} H_o(k), \tag{2}$$

where K is the total number of waypoints, and $H_b(k)$, $H_c(k)$, and $H_o(k)$ are, respectively, the height of the bridge, the coverage height, and the overlapping height corresponding to node k. The weighting factor β adjusts the impact of the overlapping height.

With the defined cost function $J(\mathcal{P})$, path planning aims to minimize $J(\mathcal{P})$. However, the inherent complexity and multimodal nature of $J(\mathcal{P})$ render traditional techniques impractical due to local maxima. Consequently, heuristic and metaheuristic methods are widely used to efficiently obtain high-quality solutions. Among these approaches, the Grey Wolf Optimization (GWO) algorithm stands out as a promising population-based metaheuristic, inspired by the hunting behavior of a wolf pack, as originally proposed in [11]. The wide use of the GWO in solving optimization problems is attributed to its conceptual simplicity, exemption from parameter tuning or derivative estimation, ease of programming, capacity for distributed parallel computing, and robustness in global search [12, 13]. Therefore, the GWO algorithm is applied in this context to generate an optimal path for the UAV.

2.4 Task execution

The task execution phase is important in the successful completion of inspection missions, serving as the operational core that coordinates various elements to achieve a fully autonomous and effective bridge assessment. Our system integrates data from path planning, utilizes precision control mechanisms, and adapts to dynamic environmental conditions during this phase to ensure mission success. In our specific setup, we deploy a 3DR Solo UAV equipped with a GoPro Hero camera. After concluding the path planning phase, we upload the predefined flight path to the UAV through the Mission Planner ground control station. The tracking mechanisms, featuring a cascade controller, enable the UAV to precisely follow the planned path. This precision is essential for capturing comprehensive bridge information in the form of high-resolution images. The collected data, primarily in the form of images, serves as a valuable resource for subsequent stages of the inspection process, such as image processing, contributing to assessing the condition of the bridge. In this paper, our main focus is on using the digital twin concepts in UAV control and path planning of bridge inspection tasks.

3 Digital Twins for UAV-based inspection

A real-world execution of UAV critical tasks such as bridge inspection requires a high level of success with utmost safety. This necessitates a time-consuming process of evaluation and field tests in restricted and sometimes risky conditions. As a promising alternative, visualization with simulation has emerged as an effective approach to test, verify, and validate UAV features in early-stage development as well as in various applications across many areas. This section introduces a co-simulation framework designed to enable autonomous UAV systems to take suitable actions in control and planning, under practical operation conditions, to enhance overall performances, including safety, before deploying them for real-world inspection tasks. The process begins with the assembly of a 3D CAD model of a UAV in Solidworks, creating a visual representation with dynamic parameters derived from geometric and material properties. Simultaneously, a digitalized version of a monorail bridge system is constructed, incorporating elements like the bridge structure and stationary obstacles (trees, railway masts, and light poles), each presenting unique navigation challenges for the UAV. These virtual components are then imported from their respective CAD files into a simulator.

3.1 Computer-aided design UAV model

Computer-aided design (CAD) is a prevalent industry practice, facilitating easy comprehension, enhancing productivity, and facilitating engineering product modifications. In this study, CAD plays a crucial role in representing the 3DR Solo UAV, a key component of the digital twin platform. Utilizing component-based and parametric modeling techniques, a modular design is achieved, ensuring seamless integration. The software captures all dynamic parameters from the product specifications and measurements, storing these numerical values in a compatible file format for future use. Securing inertial parameters through specialized instruments or analytical calculations is challenging. However, CAD modeling streamlines this process, enabling the digital twin to swiftly accommodate various UAVs and inspection environments on the platform, ensuring accuracy and versatility for simulation and analysis.

3.2 Virtual flight environment

In the realm of digital twin development for UAV systems, an essential requirement is a virtual flight environment that accurately simulates aerial vehicle motion. While existing simulators like AirSim, Gazebo, jMAVSim, and FlightGear are useful, they often lack complete dynamics representation within a visualized environment and entail substantial computational costs. Addressing these limitations, we chose Solidworks, a versatile tool for creating 3D models that seamlessly integrate into Matlab/Simulink, reducing the need for additional software dependencies. To demonstrate the capabilities of our digital twin platform, we crafted a visualized monorail bridge, a critical element of our inspection mission, incorporating virtual trees and light poles as obstacles to mimic real-world scenarios. This integration yields a comprehensive representation of the considered monorail bridge, enabling users to test and optimize inspection scenarios before real-world execution. To enhance visualization and examination of the responses from the UAV, we use spherical markers to visually represent desired waypoints from the cooperative path planning algorithm, along with the interpolated polynomial trajectory within the virtual environment.

3.3 Numerical simulation

In Section 2, we presented the vehicle dynamics, tracking controller, and path planning algorithm for our autonomous UAV system. Figure 4 illustrates the simulation model, encompassing trajectory generation and control, UAV dynamics, and environmental components. These simulations validate the preparedness of our path-planning algorithms for real-world monorail bridge inspection missions. Within the dynamic component of the UAV, we introduce inputs for fault injection during its assigned inspection mission. An examined defect in our study was unexpected motor failure, influencing dynamic calculations for UAVs. Our digital twin incorporates built-in safety mechanisms to monitor real-time motor motion. Upon anomaly detection, a trigger initiates embedded emergency landing strategies in the simulator, safeguarding inspection equipment and ensuring ground personnel safety.

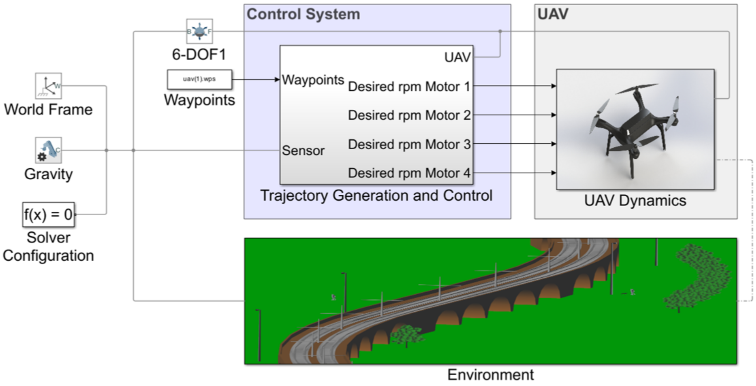


Figure 4. Simulation model

4 Results

4.1 Case study

To demonstrate the capabilities of our digital twin model, we conducted a virtual inspection of a monorail system located at Wentworth Park, New South Wales, Australia, with coordinates −33.875266°S, 151.192769°E. The viaduct supporting the entire railway system was constructed, and obstacles such as trees and light poles were strategically placed based on satellite-captured images. Our objective is to deploy a UAV, configured with take-off and landing locations, to execute an inspection task. Our approach utilizes the GWO algorithm to generate optimized, collision-free routes while considering environmental obstacles, as depicted in Figure 5. To ensure the safe maneuvering of UAVs, we implemented red cylinders to delineate threat zones around obstacles. Additionally, a cascade trajectory tracking controller is employed to guarantee precise adherence to planned routes by continuously monitoring the position and velocity of the UAV, making necessary adjustments to ensure it remains on track.

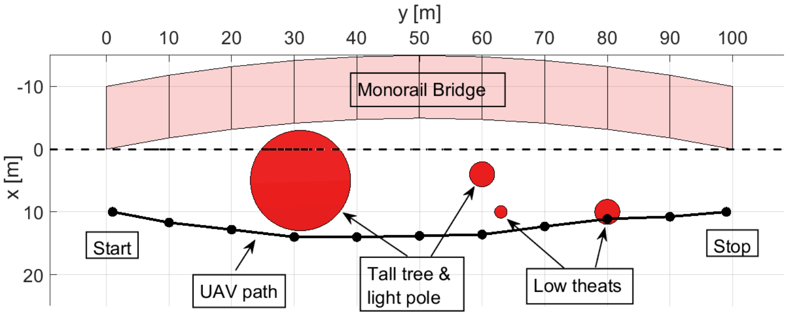


Figure 5. Generated path

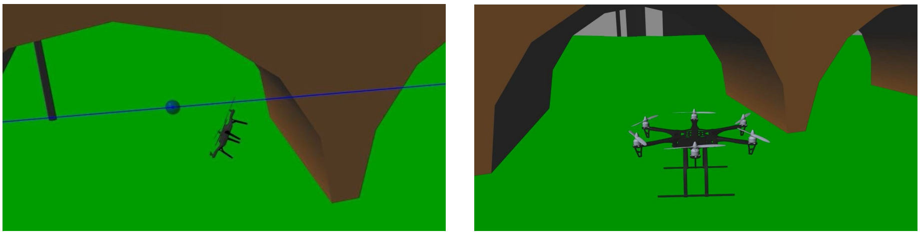
4.2 Inspection visualization

In the conducted test, a UAV equipped with cascade controllers successfully executed its inspection path by precisely tracking its reference trajectory. To assess the resilience of the controller against external factors such as winds, random disturbances were introduced into the simulation model, evaluating the UAV response. Leveraging the proposed digital twin platform enables the virtual assessment of UAV performance, control algorithms, and trajectory tracking, providing a foundation for continuous improvement. Figure 6 illustrates a simulation scenario, demonstrating the ability of the UAV to follow its reference trajectory while efficiently avoiding obstacles. This practical application of UAV-based monorail bridge inspection highlights the potential of digital twin technology in enhancing environmental sustainability and advancing engineering.

To underscore the effectiveness of the digital twin, we conducted an additional simulation involving a malfunctioning motor in the UAV. In this test scenario, we deliberately disconnected the electrical signal to one of the motors mid-flight. The resulting outcome is visualized in Figure 7a. As anticipated, the 3DR Solo UAV, employing cascade PID control, was unable to sustain its flight and descended to the ground. For enhanced fault tolerance operations [14], it is recommended to explore alternative UAV configurations with additional rotors, such as hexacopters or octocopters, to increase redundancy in generating thrust force. Consequently, the UAV is capable of executing a safe landing, as illustrated in Figure 7b.

(a) Virtual UAV during the experiment (b) Virtual bridge image captured from UAV

Figure 6. Simulation result



(a) Quadcopter (b) Hexacopter

Figure 7. UAV in a faulty operation

4.3 Experimental verification

In our experiments, we employed a 3DR Solo UAV equipped with a 3-axis gimbal and a GoPro Hero 4 camera, facilitating detailed inspections of complex and challenging areas. The UAV featured dual Cortex M4 processors for control and an ARM Cortex A9 for flight operations, all managed through QGround Control software. This setup enabled autonomous flight and streamlined data analysis, including predefined flight paths and waypoints. The experiment aimed to assess the effectiveness and efficiency of UAV-based inspection for railway bridges in a realistic flight environment. Figure 8 displays the UAV during the experiment and a bridge image captured from the UAV, showcasing a striking resemblance to the results obtained from earlier digital twin simulations. This consistency underscores the precision and reliability of UAV-based inspection in defect detection. Furthermore, adopting UAV-based inspection significantly reduces inspection time while providing comprehensive and precise bridge condition data. These findings indicate that UAV-based inspection has the potential to enhance infrastructure monitoring, improving efficiency and accuracy while mitigating the costs and risks associated with manual methods.

(a) UAV during experiment (b) Bridge image captured from UAV

Figure 8. Experimental result

5 Conclusions

This research has investigated the integration of UAVs and digital twins as a promising solution for bridge inspection. Through comprehensive simulations and real-world testing, our approach has demonstrated exceptional accuracy, efficiency, and resilience. The combination of digital twins replicating real-world scenarios and the autonomous flight of UAVs holds promise for streamlining infrastructure inspection, significantly reducing operational complexities, and enhancing environmental sustainability. This synergy represents a viable approach to reshape the infrastructure management landscape, delivering a future marked by greater accuracy, as well as reduced costs and risks in the field of inspection and maintenance practices. In future research, we will explore cooperative multi-UAV missions and advanced sensing technologies to further enhance bridge inspection performance.

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