Bridge Inspection Strategies Analysis through Human-Drone Interaction Games

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ABSTRACT

Bridge inspections are characterized by their labor-intensive nature and inherent risks, relying predominantly on engineers' visual analysis. Although the integration of drones has alleviated the safety concerns associated with human labor, the accurate identification of defects in vital elements continues to necessitate inspectors' specialized knowledge. Aggregating multi-inspector experiences can improve the localization of critical defects. The challenge lies in capturing and explaining drone trajectories into reusable and explainable strategies. This paper presents a framework to capture inspectors' strategies by analyzing drone control in bridge inspection simulations. It gathers and scrutinizes inspectors' drone control histories to understand their intentions. Due to the vast search space of inspection strategies in dynamic, uncertain contexts, imitation and reinforcement learning are utilized to learn reusability and explainability. Experiments demonstrate that drone trajectories aligned with bridge elements can explain inspection knowledge. Inspectors with explainable patterns, such as the human attention between the different spans inside the span, achieve better defect detection performance (correlation coefficient of 0.5). This framework promotes inspector-drone collaboration that adaptively supports human inspectors, resulting in more reliable inspections.

INTRODUCTION

A considerable number of commonly utilized bridges have exceeded their intended design longevity. Bridge inspection with drones is a relatively new technology that has gained popularity in recent years for its numerous advantages over traditional methods of bridge inspection to improve safety, efficiency, and cost-effectiveness. Traditionally, highly skilled pilots and inspectors must control drone missions to ensure sufficient inspection outputs. Drones are small, unmanned aircraft that can be remotely controlled and equipped with various sensors and cameras to gather high-resolution images and data from hard-to-reach or dangerous areas (Rakha and Gorodetsky 2018). It allows engineers to quickly identify and address any potential problems to ensure the safety and stability of the bridges for the public.

Although drones are capable of autonomous mode, it is imperative to incorporate human inspectors in the control loop to ensure the coverage of critical areas of a given bridge. The on-site inspection environment can be complex, with various factors, including weather, traffic, and bridge structures, that require attention. Human inspectors may miss defects in such environments, leading to inconsistent inspection behaviors, conflicting condition assessments, and biased maintenance plans. Despite the ability of drones to capture high-quality images of a bridge from a distance, the control and expertise of a skilled inspector or pilot remain essential.

Incorporating human inspectors in the drone inspection process is crucial for ensuring accurate and reliable results, making it a vital component of bridge inspection practices" (Hopcroft et al., 2006). Research on using drones for bridge inspections often focuses on the drones' technology and the utilization of image processing and computer vision for data analysis, focusing less on the role of human inspectors. In practice, drones enhance inspectors' capabilities rather than replacing them. Even though drones can operate autonomously, including human inspectors in the inspection process can improve safety, efficiency, and effectiveness. In some situations, inspectors may need to take control of the drone, such as identifying potential issues with the bridge that require additional data to be collected. Also, inspectors may need to take control in response to unexpected situations or sudden needs identified by the inspector or an artificial intelligence model. Previous studies show that more experienced inspectors tend to be more consistent in inspection results. Behavioral studies in other domains indicate that machines have the potential to understand and learn from humans and cooperate with them.

To ensure the reliability of drone-based inspections, it is critical to leverage inspectors' expertise and aggregate multi-inspector experiences (Liu et al. 2022, 2023). Tracking and sharing how experienced inspectors control the drone to find the defects could share and explain the inspection strategies supported by their knowledge of the structure. The drone with AI has the potential to learn from inspector's inspection strategies to achieve more accurate bridge inspections with crack detection and locations. The challenge lies in: (1) capturing and explaining the trajectories of drones in a changing and uncertain context; (2) reusability and explainability of the inspection strategies learned by imitation and reinforcement learning. Unfortunately, these studies have not explored the relationship between behavioral inspection processes and the bridge component to explain the inspectors' intentions.

This paper (1) designs a digital drone-based bridge inspection game for accurately representing and collecting the inspectors' behaviors and inspection results; (2) to represent the inspection knowledge from the inspectors' behavioral data; The research questions are: 1) *How to capture detailed inspection process behaviors of inspectors?* 2) *What is the inspectors' knowledge, and how do they present the inspector's knowledge and transfer it to the AI-based drone for more accurate defect locations*? Several technical obstacles hinder the resolution of these two research inquiries. First, capturing detailed drone-based inspection process behaviors of inspectors in various contexts of structural condition assessment is difficult because field scenarios that collect the drones' flying trajectories could hardly connect with the semantic information of the bridge. A critical challenge is how to relate the data acquired by the drone to the microscopic observations documented in inspection reports. Second, no knowledge representation method exists for extracting meaningful inspection strategies from behavioral process data for bridge inspection.

LITERATURE REVIEW

Bridge inspection with drone behavior capturing. In traditional drone missions, highly skilled pilots and inspectors are required to ensure sufficient inspection outputs. The on-site environment is complex, with factors such as illumination, traffic, weather conditions, and different types of bridge structures, making it critical to keep inspectors in the control loop. Drones provide high-quality and accessible data on the object of interest. With a semi-autonomous flight plan, they can capture high-resolution images and cover the whole body of the structure, getting closer to critical areas. Lapointe et al. believe combining drone navigation with AI and AR technologies can improve inspection efficiency, spatial accessibility, and automated inspection capabilities (Lapointe et al. 2022). Marshall University's prototype bridge inspection research for drones (BIRD) aims to minimize human involvement and improve the overall efficiency of bridge inspection throughout the bridge inspection process.

Some incidents show the potential of a drone inspection to improve bridge inspection reliability. The Hernando DeSoto I-40 Bridge in Memphis, one of two major interstates crossing the Mississippi River, was closed in May after large cracks in steel girders were discovered by Lorie Tudor. The Arkansas Department of Transportation later announced that the closure was due to the failure of a bridge inspector to detect the significant cracks that appeared in 2019 and 2020. As a result, that inspector was subsequently fired. This incident highlights the discrepancy between manual inspection reports and drone inspection videos.

Drone path planning is an essential aspect of bridge inspection using drones. It involves determining the optimal route for the drone to navigate while capturing images or collecting data on the bridge's condition. The path planning process considers the bridge's shape, size, location, and the drone's flight capabilities, safety protocols, and regulations. However, it is up to the inspectors to decide the object of interest or critical areas, and if they are not determined correctly, defects on the bridge may be missed. Failure to detect defects could lead to inconsistent bridge inspection behavior, conflicting condition assessments, and biased maintenance plans. As a result, the reliability of drone-based inspections still depends on inspectors' knowledge.

Inspection knowledge. Visual inspection is the careful and critical assessment of an object concerning a predefined standard. During the visual inspection, inspectors need mentally process, concentrate, and transmit information with exclusive use of short-term and long-term memory. Short-term memory is for remembering which locations or components have been inspected, and long-term memory is for recalling the original conditions of the studied components and related standards. Bridge visual inspection relies on 'tacit knowledge,' an intrinsic understanding of how things work that intuitively enables inspectors to produce strategies and solutions in new circumstances. Unlike the 'explicit knowledge' that could be described and presented in instructions, handbooks, or standards, tacit knowledge is learned by observation, imitation, and practice, which is difficult to communicate or formally record or share. The unclear definitions or instructions for visual inspection force inspectors to use their subjective judgments or assessment criteria, which would cause incorrect, inconsistent, or lower reliable outcomes. Little research has explored the method to collect and present tacit knowledge for visual inspection. Unfortunately, limited studies examined inspectors' detailed behavior processes deriving critical defects and underlying reasons from available bridge project data to understand the bridge inspection strategy.

Human-drone Interaction. Human-Drone Interaction (HDI) is an emerging field that concentrates on the interplay between humans and drones. The rising utilization of drones across diverse sectors has highlighted the necessity for effective and secure HDI methods. One notable trend is the growing prevalence of human-drone collaboration in infrastructure inspections. Incorporating drones into inspections reduces human involvement while simultaneously boosting overall process efficiency. However, humans remain indispensable in the intelligent inspection process, as technology cannot entirely replace them. As the demand for safer and more efficient inspections escalates, integrating drone and AI technologies in infrastructure inspections is poised to become more commonplace. Nonetheless, striking the right balance between leveraging AI's advantages and avoiding excessive reliance on technology is crucial. The ideal approach lies in maintaining a proper equilibrium between AI assistance and human oversight. Reinforcement learning (RL) and imitation learning (IL) are two prominent machine learning techniques that have been employed in HDI to enhance drone performance and Interaction with humans. A key challenge for both RL and IL in HDI is ensuring efficient and safe collaboration between humans and drones. For instance, during a drone-assisted bridge inspection, the drone can initially learn from a human demonstration how to examine the bridge, identify defects, and navigate the environment securely. Subsequently, reinforcement learning can be applied to further optimize the drone's path planning and inspection strategy based on feedback from the inspection process (Ke et al. 2021; Yang et al. 2019). This approach can lead to a more efficient and secure inspection process, requiring less human intervention while delivering more effective performance in detecting and classifying defects.

METHODOLOGY

This paper presents a framework for capturing and sharing the inspectors' inspection strategies by analyzing how inspectors control drones in a bridge inspection simulation game. This framework aims to investigate how inspectors control a drone in similar scenarios automatically and track inspectors' drone control techniques can explain the inspection strategies supported by their knowledge and understanding of the structure. The framework, illustrated in Figure 1 below, consists of four steps: (1) gamification of a bridge inspection, (2) inspector behavioral capturing and processing, and (3) human-drone interaction.

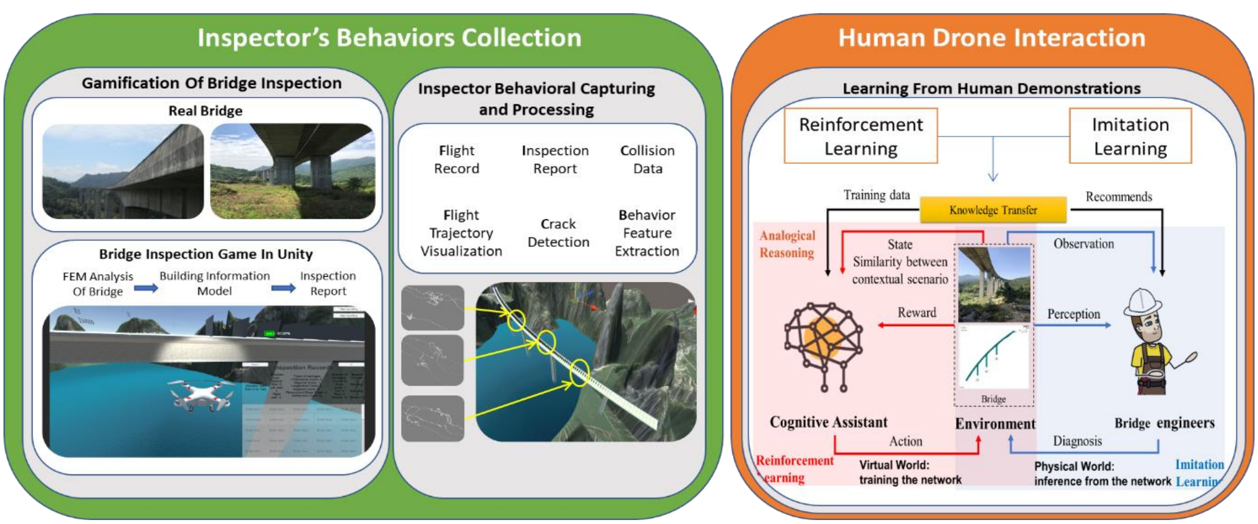


Figure 1. Framework for digital bridge inspection with human-drone Interaction.

Gamification of bridge inspection from multi-modal data. This bridge inspection game was subsequently developed based on the research from Li's work (Li et al. 2022). The bridge inspection game combined with data from multi-modal, including the finite element model (FEM) of ANSYS to get the element positions, displacements, and stress, the geometrical information from Revit and crack image, and locations from the inspection reports to design the bridge inspection game with a drone. The cracks were placed according to the analysis results from FEM and the crack locations.

Inspector behavioral capturing and processing. During the simulated bridge inspection, the inspection strategy, including the timestamp, the drone flight data (position, velocity, and remaining battery level), the sequences of inspected bridge elements, and the inspection records (defects locations, structure type, types of defects, severity of defects and reasons).

Reinforcement learning and imitation learning for learning from inspection trajectories. Reinforcement learning and imitation learning can be used together in human-drone Interaction to combine the benefits of both approaches. The drone first learns from human demonstrations using imitation learning. Then, reinforcement learning is used to fine-tune the available policy and improve its performance. Using imitation learning to provide an initial approach and reinforcement learning to refine it, "learning from demonstration can accelerate the convergence to a good inspection strategy compared with RL that typically are computational expensive.

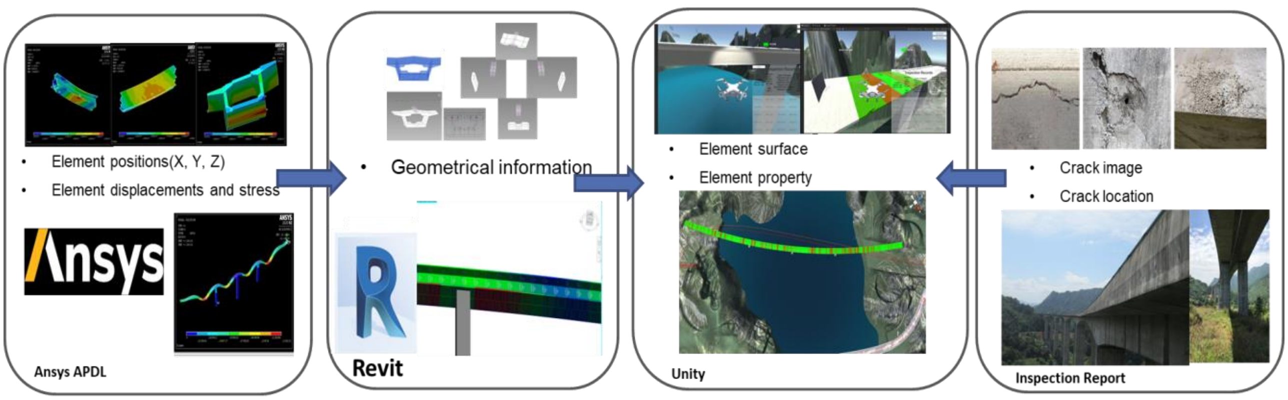


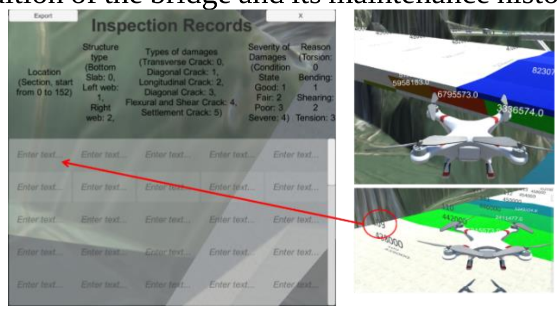
Figure. 2. Multi-model data integration-based bridge inspection gamification

EXPERIMENTAL RESULTS AND DISCUSSION

Gamification of Bridge Inspection for Behaviors Collection.

- **Crack simulations analysis based on FEM and inspection reports:** According to the crack locations in the inspection reports, FEM has been applied in bridge inspection to simulate the behavior of the bridge under different loads and conditions, allowing create reasonable potential cracks and defects to be identified.
- **Bridge inspection environment built up in Unity:** Unity is a game engine commonly used to develop video games and simulations. Unity can generate 3D models of the bridge structure and simulate various inspection scenarios in the context of a bridge inspection. The process of inspection environment in Unity involves importing the bridge geometry, defining the material properties, adding inspection elements, and implementing the inspection logic. These models accurately represent the bridge structure and inspection scenarios, providing inspectors with a realistic and interactive training environment.

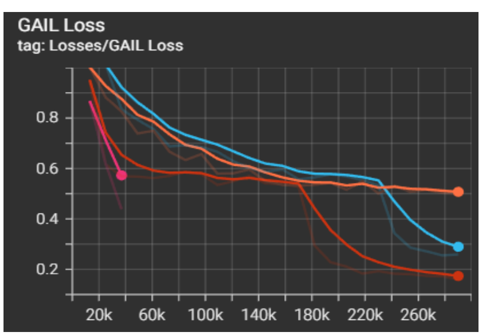
- **Drone inspection (defect information collection, flight trajectory record):** The drone inspection process in the bridge inspection game involves the operation of a drone to find the bridge cracks in a third-person perspective to simulate the bridge inspection process, as shown in Figure 3 (a). The drone's flight data is recorded using Unity's log files to extract critical behavioral information from the raw data.
- **Fill in the inspection record:** The participant is requested to fill in the inspection records about any detected defects, such as the location and severity of the defects, based on their understanding of bridge inspection, as shown in Figure 3 (b). Inspection records can provide valuable information about the condition of the bridge and its maintenance history.



a. Bridge cracks detection with drone b. Fill in the inspection records

Figure. 3. Illustration of bridge inspection game with drone

Human-Drone Interaction for learning from inspectors' strategies. The mapping between the drone flying trajectory and the geometric information of the bridge could also generate some reusable behaviors that can guide drones to learn those behaviors. We define the drones' state, action, and basic reward to transfer the inspector's inspection strategy. The drone is equipped with a laser sensor to detect the surrounding bridge components and defects. The state is the feedback of the laser sensor, which is encoded in the one-hot encoding. The action is the control action of the drone. Because the reward is difficult to define in different contexts, we define the basic mechanics of the reward, such as finding one defect that will get the reward. The drone can initially learn how to examine the bridge, identify defects, and navigate the environment securely from a human demonstration. Subsequently, reinforcement learning can be applied to further optimize the drone's path planning and inspection strategy based on feedback from the inspection process.



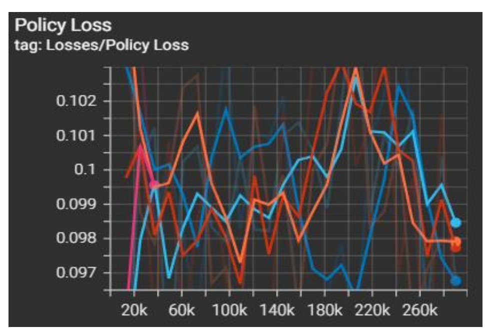


Figure. 4. The training process of imitation learning for bridge inspection with drone

Figure 4 shows that the loss of Generative Adversarial Imitation Learning (GAIL) and policy loss decreases significantly as the training progresses. In GAIL, the learning process is modeled as a two-player game between the generator (the agent) and the discriminator. The GAIL loss function helps to quantify the difference between the agent and the expert behavior, guiding the agent to act more like the expert. In the context of policy gradient methods, the policy loss is a measure of how much the current policy (the strategy the agent is following to select actions) deviates from the optimal policy. The aim of the learning process is to adjust the parameters of the policy in a way that minimizes this loss, thus making the policy more optimal over time.

Illustration of the learned drone trajectories for understanding the bridge inspection strategy. A sound strategy for bridge inspection aims to maximize inspection coverage and accuracy while minimizing inspection time and cost. In this simulation experiment, the key indicators are detection integrity (i.e., the number of detected cracks in proportion to the total number of simulated cracks), detection accuracy, detection time, and drone safety (i.e., the number of collisions with the bridge). The detection behavior is evaluated visually by visualizing the flight trajectory. An effective inspection strategy involves clearly defining inspection objectives, choosing appropriate inspection methods, developing an inspection plan, and optimizing drone pathfinding. Figure 5 shows the drone trajectory capturing some explainable inspection patterns. The inspected bridge is a five-span bridge with three middle and two side spans. The inspector found the similarity between the three middle spans and also noticed that the bottom slab and side webs in the middle spans are usually under high tensions and shearing forces. It is highly likely to have defects in these elements. Therefore, the inspector controls the drone to hover in the bridge's middle span, and the drone trajectory shows three clusters in three different middle spans. The mapping between the drone flying trajectory and the geometric information of the bridge (the sequences of the inspected bridge elements) could explain the inspectors' inspection strategy.

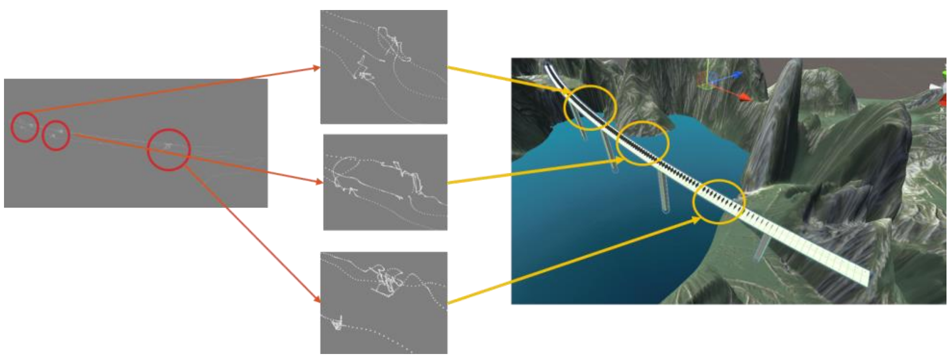


Figure. 5. Drone trajectory visualization and analysis

The authors defined the fitness to measure the similarity between the inspectors' inspection patterns with the found explainable patterns. Figure 6 shows that the inspector with the explainable patterns (high fitness) is likelier to have better defect detection performances (an average correlation coefficient of 0.5 indicates a moderate correlation between the pattern and the defect detection performances).

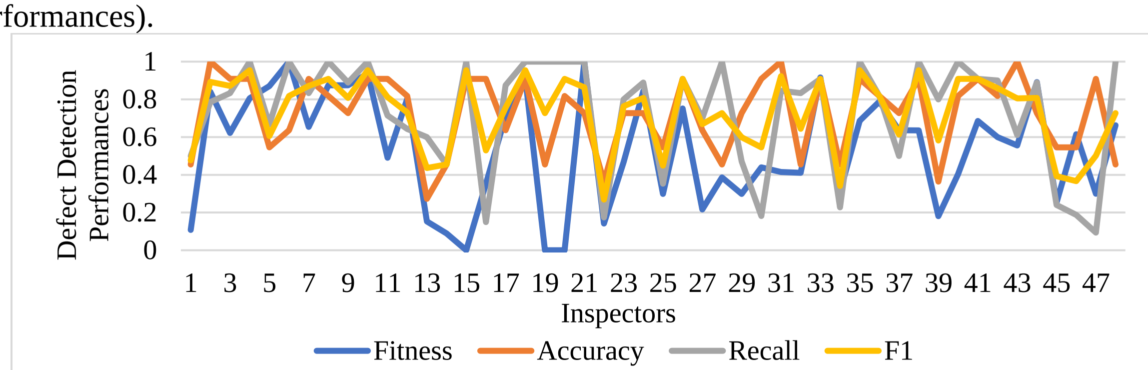


Figure. 6. The relationship between the inspection strategy and the defect detection

CONCLUSION AND FUTURE WORK

This paper designs a bridge inspection game from multi-data (BIM, FEM, and inspection reports) for addressing the challenges of capturing detailed inspection process behaviors of inspectors. The framework enables inspector–drone cooperative process analytics to generate AI agents that can adaptively assist human inspectors in bridge inspection. The summary of the findings includes 1) due to the ample search space of inspection strategies, reinforcement learning cannot guarantee the drone finds all the defects. Integrating imitation learning and reinforcement learning can overcome this problem by finding practical searching trajectories. 2) the inspection strategies learned by imitation and reinforcement learning are explainable and reusable. 3) the inspector with the explainable patterns (high fitness) is more likely to have better defect detection performances (an average correlation coefficient of 0.5 indicates a moderate correlation between the pattern and the defect detection performances).

The limitations for this paper are (1) this paper focuses on learning inspection strategies without explanation mechanisms that need a predefined ontology. In the future work, we would define an ontology to represent the inspection process. The finding of this paper could help us define the ontology that help explain the inspection process patterns reusable and traceable to bridge knowledge that help inspectors decide their inspection strategies. (2) More sensitivity analyses are needed to test to decide the best setting (state, action and reward) for reinforcement learning and imitation learning.

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