Transforming Bridge and Railway Asset Management A Case Study of the Rideau River Railway Bridge Inspection Using Advanced Drone Technology and AI

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Abstract

The Rideau River Railway Bridge is a railway plate girder bridge that spans the Rideau River in Smiths Falls, Ontario, Canada. Currently owned by the Canadian National Railway (the successor to the Canadian Northern Ontario Railway), the bridge supports various rail services, including the Via Rail Toronto–Ottawa Corridor passenger trains.

Niricson conducted the first of two concrete condition assessments on the Rideau River Railway Bridge in May 2024. This initial survey aimed to provide a baseline analysis of the bridge's condition, focusing on the identification and quantification of visual defects and delamination. The data collection process involved capturing high-resolution RGB/optical images and acoustic soundings which were both collected by a robotic system. The data was subsequently processed using a defect detection and quantification software. A second survey was completed in October of 2024 to identify any changes and validate change detection capabilities. An additional software was used on the dataset to identify any geometrical deficiencies to the rail track.

The purpose of the project was to demonstrate the capabilities of a digital condition assessment, validate the capability of the acoustic sensor, and validate the repeatability for a digital assessment.

1. Introduction

The Via Rail bridge located at 44°53'30.81"N, 76°00'14.35"W in Smiths Falls, Ontario, is a historic railway structure that spans the Rideau River. Constructed between 1912 and 1913, this bridge is a traditional through plate girder design, supported by concrete piers and abutments. It was originally part of the Canadian Northern Railway's route connecting Toronto and Ottawa. Today, it remains in use for Via Rail's passenger services, providing a vital link for traveler. The bridge is a 5 span bridge with 4 concrete piers, and steel girders. The location of the bridge is shown below:

Figure 1. Via Rail Bridge (Over Rideau River in Smiths Falls Ontario), 44°53'30.81"N / 76° 0'14.35"W

Historically, bridge condition assessments have relied on visual assessments carried out by engineers using rope access, scaffolding, or lift equipment. These methods are labor-intensive, subjective, and may yield inconsistent results between surveys. More importantly, they expose workers to significant safety risks and require costly traffic or rail service interruptions. Oftentimes, detailed quantities about crack lengths and widths, or material loss are not captured. This leads to significant challenges in inspection comparability, especially if inspections are completed by different personnel over time.

Emerging technologies in photogrammetry, robotics, and artificial intelligence (AI) are enabling enhanced asset management and inspection capabilities. Robotic and photogrammetry-based inspections provide rapid, safe, and comprehensive data capture, while AI algorithms allow for consistent detection and quantification of structural defects. When combined with digital asset management platforms, these technologies facilitate predictive maintenance and optimized resource allocation.

This paper presents a case study of the Rideau River Railway Bridge, inspected by Niricson in collaboration with DecisionWorks (drone pilot), and Transport Canada, and demonstrates how robotic systems, photogrammetry, and artificial intelligence tools can offer an enhanced alternative for bridge condition assessments.

2. Scope of Assessment

2.1 Scanned Areas

The project scope included collecting imagery data from all surfaces of the concrete structure, and collecting sounding data from specific surfaces. The team scanned Piers 1 through Pier 4, capturing all faces using a DJI M300 with a Zenmuse P1 camera with a 35mm lens. For testing purposes, data from Pier 2 and Pier 3 were also collected using Skydio X10. Two takeoff locations were set – one on each side of the river. This helped ensure the pilots maintain visual line of site with the UAV throughout the condition assessment. The site sectioning defined the structural components as outlined below:

Figure 2, Rideau River Bridge Site Sections

3. Methodology

3.1 Survey Control and Data Collection Methods

Ground control points were set at various location throughout the site and at accessible portions of the structure. Local survey monuments were used, and new ground control points were set as needed. Ground control points (GCPs) improve the accuracy and reliability of photogrammetry-based condition assessments and 3D mapping. GCPs are fixed, precisely surveyed markers placed on the ground that serve as reference points for aligning aerial imagery with real-world coordinates. By incorporating these points into its data processing workflow, Niricson ensures that the spatial models and measurements derived from imagery are highly accurate, consistent, and georeferenced. This allows for precise defect localization, repeatable condition monitoring over time, and integration of inspection results with engineering design or asset management systems. An example of a ground control point, visualized in a bridge 3D model, is shown below:

Figure 3. Example of Survey Target, Visible in 3D Model

Niricson uses crack gauges as part of its validation process to ensure the accuracy of crack width measurements captured through its advanced imaging technologies. Crack gauges, which provide precise physical measurements of crack displacement, serve as a ground-truth reference against which digital or automated measurements can be compared. By deploying these gauges in the field and cross-referencing the recorded data with readings from their AI tools, Niricson can confirm the reliability of its crack width assessments. This validation step supports compliance with engineering standards and strengthens confidence in the digital inspection results. An example of a crack gauge, visible in a digital 3D Model, is shown below.

Figure 4. Example of Crack gauge, visible in 3D model

3.2 Imagery Dataset

Ground Sampling Distance (GSD) in photogrammetry refers to the physical size of one pixel on the ground in a captured image. Essentially, it defines the spatial resolution of aerial imagery, indicating how much real-world distance is represented by each pixel. A smaller GSD means higher resolution, allowing finer details, like cracks or small features, to be detected more accurately, while a larger GSD reduces detail but covers a wider area per image. GSD is determined by factors such as camera sensor size, focal length, and distance from structure.

For this project, the team collected the data at 0.7mm ground sampling distance (GSD). This GSD allowed ultra-high-resolution imagery the ability to detect small crack features down to 0.3mm with proper ground truth data. Flying with the Zenmuse P1 Camera with a 35mm lens, this would indicate flying approximately 4 meters away from the structure. The imagery was captured with 70% sidelap and 70% frontlap. Frontlap and sidelap describe the amount of overlap between images to ensure complete coverage and accurate 3D reconstruction. This overlap allows the photogrammetry software to match features across images and build a continuous model of the structure or terrain. Adequate coverage is essential for producing detailed 3D models, as they allow each point on the ground to be captured from multiple angles and perspectives.

The team tested both the Skydio X10 and the Zenmus P1 Camera for this project to determine which one would result in higher quality. An issue faced by the team was image distortion. This is often related to pilot error but can also be a result of challenging site conditions and the equipment being used. In this case, image distortion was found to be caused by the camera equipment being used. To address this distortion, Niricson made the decision to test a variety of camera systems to achieve higher-quality data. The two systems were the 1) Zenmuse P1 Camera and the 2) stock Skydio X10 camera. The specifications for each are listed in the table below:

Specification	**SKYDIO X10 Camera** **(VT300-L 1" Module)**[8]	**Zenmuse P1 Camera**[9]
Sensor Size	25.4mm x 25.4mm	35.9mm x 24mm
Shutter Speed	Mechanical: Not Applicable, Rolling Shutter Electronic: 1/8000 -1s	Mechanical: 1/2000 – 1s * Electronic: 1/8000 -1s
Aperture Range	f/1.95	f/2.8-f/16
ISO Range**	100 to 16000	100 to 25600

Table 1. Camera Specifications Comparison

*Only available for aperture value no larger than f/5.6 (higher aperture indicates less light entering camera).
** A higher ISO means that camera sensor is more sensitive to light, so it needs less light to create a well-exposed photograph. However, a high-ISO can also introduce more digital noise and reduce color vibrancy

The following images are the results of the two tested imagery systems. Both images were collected at 0.7mm/pixel GSD and with similar data capture settings: 1) Drone stops and capture each photo, and 2) similar ISO and shutter speed settings. However, as is visually apparent, the Zenmuse P1 data performed with higher clarity and crispness than the X10 camera. As a result, the Zenmuse P1 camera was selected for the operation, resulting in higher quality quantification and detection of visual defects.

Figure 3. Image Quality Comparison X10 camera and Zenmuse P1 camera

As demonstrated in the tables and figures above, camera type, vehicle, capture speed, camera aperture, pilot expertise, and a variety of other factors can result in different outcomes when it comes to quality and the ability to detect defects. As a result, the team decided to proceed with using the data from the Zenmuse P1 Camera data.

Once the imagery was captured with proper frontlap and sidelap, the adequate ground sampling distance, and coverage of the proper structural elements, the imagery data was organized and processed using server-grade processing power to stitch the images into a 3D model. The 3D model for Rideau River Railway Bridge is shown below:

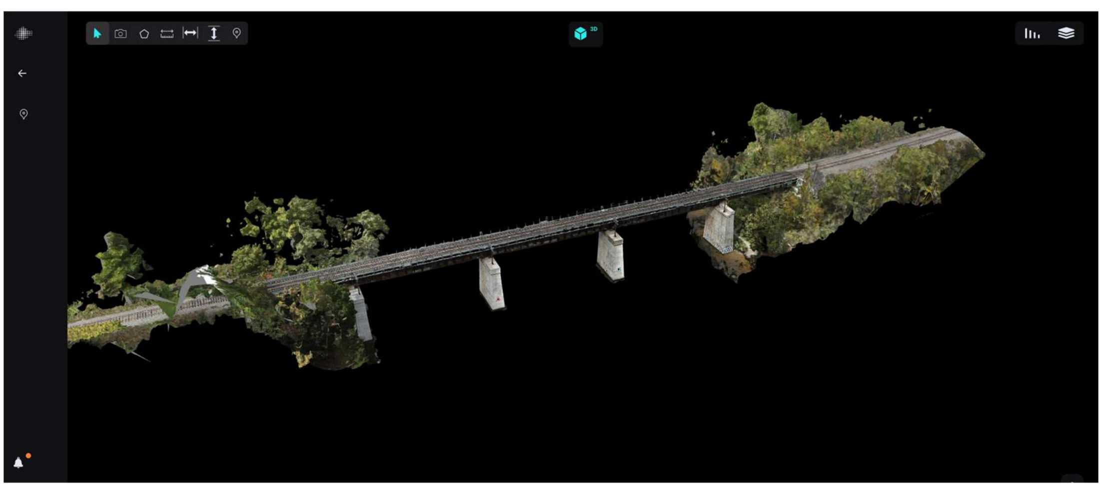

Figure 5. 3D Model, Rideau River Railway Bridge

3.3 Robotic Acoustic Soundings

Niricson's NCX Mini is a compact, UAV-mounted acoustic sensor designed to simulate the traditional concrete hammer test for detecting delamination in concrete bridges. This tool strikes the concrete surface at a rate of 20 taps per second, enabling rapid data collection in hard-to-reach or hazardous areas that are challenging for manual inspections. The NCX Mini employs a high-sensitivity microphone to capture the acoustic response from each strike, which is then analyzed using machine learning algorithms and manual quality control to identify potential delamination zones. Using onboard cameras, the sensor provides georeferenced delamination maps that assist asset owners in monitoring structural integrity over time and can be brought into the AUTOSPEX visualization software.

For the Rideau River Bridge, the data collection team collected acoustic data using the NCX Mini drone-mounted sensor from Pier 1 (West face), Pier 3 (East face), and Pier 4 (North, East, South faces). The purpose was to identify anomalies on the structure and validate the results of the delamination map generated from the sensor

Figure 6. NCX Mini modeling and development in the Lab at Niricson

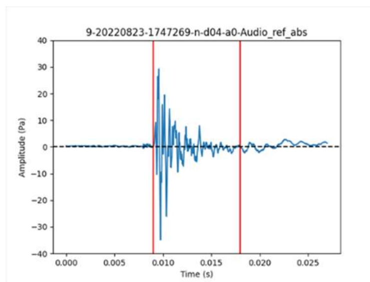

Figure 7. Example of a Time Domain Signal from Delaminated Concrete

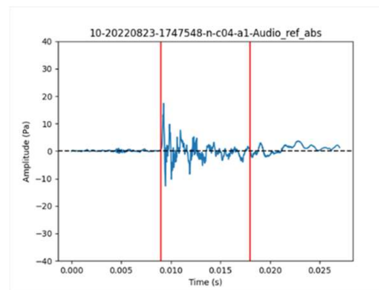

Figure 8. Example of a Time Domain Signal from Sound Concrete

For this project, validation was completed by benchmarking the NCX Mini concrete sounding technology sensor outputs against traditional hammer-sounding and chain-drag methods that are widely used in bridge and concrete infrastructure inspections. The system also undergoes calibration in controlled test environments where known defect conditions are introduced into concrete specimens, allowing sensor performance to be measured against a ground-truth standard.

The sounding results are also assessed for repeatability across multiple bridges to confirm consistent detection accuracy. This provides asset owners with confidence that automated data matches or exceeds the reliability of traditional inspection methods. The Figures below show an example comparison between the robotic sounding capability and the traditional sounding capability deployed on the soffit of a bridge structure.

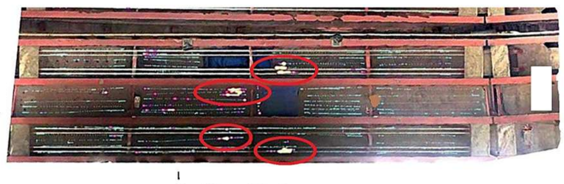

Figure 9. Acoustic Sounding from NCX Mini, with Delamination indicated in White (circled in red), the Tarps indicated in Dark Blue, and the Inspected area in Light Blue

Figure 101. Acoustic Sounding from Third-Party Hammer Tapping, with Delamination Indicated in Purple and the Blue areas Representing Areas with Tarps over Them

4. Results and Insights

The collected imagery and acoustic sounding data was processed using Niricson's AUTOSPEX™ – an artificial intelligence software for automatically mapping and quantifying, as well as visualizing, anomalies in bridge infrastructure. AUTOSPEX™ uses a deep learning model to detect and quantify defects automatically. The model becomes more powerful as it collects more data over time. The model is also supported with a manual quality control procedure to reduce and eliminate false positives and false negatives that may be identified by the algorithm and further strengthen the algorithm.

The software 1) generates a 3D Model, 2) Separates the structure into 2D Structural elements, and 3) Generates defect maps. Clients can then access the system to visual the 3D model, 2D Maps, and defect maps. As shown defect maps include the location and quantification of the surface/subsurface defects. An example of the data is shown below:

Figure 11. 3D Model on AUTOSPEX

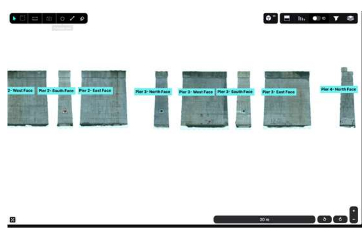

Figure 12. 2D Optical Maps Generated on AUTOSPEX

Figure 134. Defect Maps Generated on AUTOSPEX

The artificial intelligence model performance may depend on the quality of the data, lighting conditions, and other factors. In these instances, algorithms can be fed with additional site-specific data to improve the defect mapping results. The table below shows how the algorithm performed moderately for cracking and efflorescence on *Anonymous Structure 1 and* poorly for honeycombing and spalling, but fine-tuning drastically improved the outputs. Meanwhile, the results for *Anonymous Structure 2* were at a higher accuracy, meaning fine-tuning of the algorithm was not necessary.

Defect Type	Anonymous Structure 1 ML Algorithm, Percentage Accuracy (Before QC and Fine Tuning)	Anonymous Structure 1, after ML Algorithm Fine tuning	Anonymous Structure 2 ML Algorithm, Percentage Accuracy (before QC and Fine Tuning)
Cracking	**73%**	**94%**	**91%**
Efflorescence	**81%**	**95%**	**92%**
Honeycombing	**32%**	**90%**	**n/a**

Spalling	**37%**	**89%**	**n/a**

Table 2.Algorithm Performance Comparison across Two Different Structures, with Fine Tuning of Algorithm on One Structure

Based on the mapping of the defects with the algorithm, key findings from the condition survey included the following. First, a total of 4,306 individual cracks were identified, with an estimated combined length of approximately 2,988 meters. Cracks were typically in a spider-web pattern across the piers. An example of the patterned cracking found on the bridge is shown below:

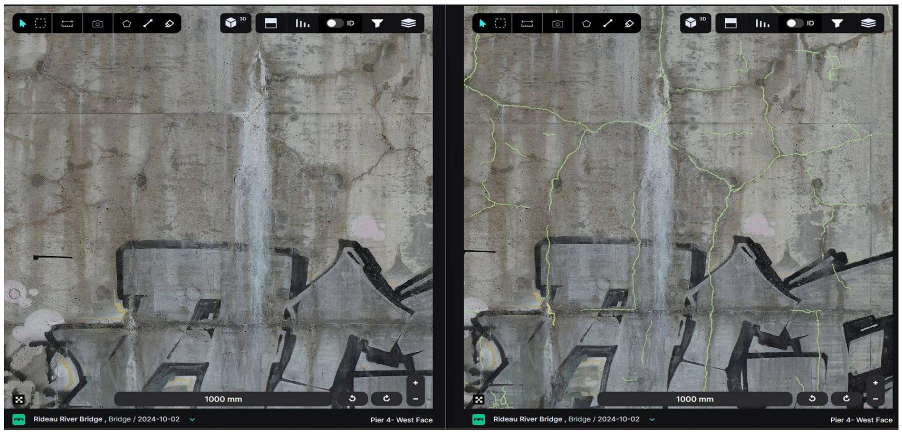

Figure 14. Rideau River Bridge, Crack Maps

For spalling, the survey detected 745 spalling defects, covering a total area of 11,647 cm^2. The spalls tended to form around features located within the east and west facing portions of the piers. An example is shown below:

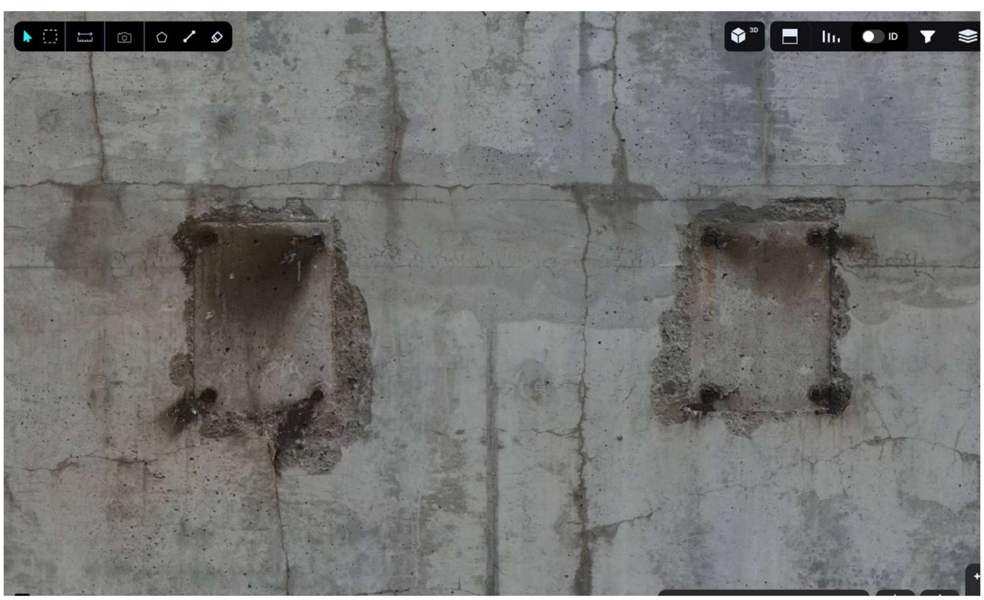

Figure 15. Spalling/Material Loss located on Bridge Features

Potential Concrete delamination (Acoustic soundings), identified by the robotic sounding device, found 29 areas as potentially delaminated, with a total estimated area of 12,631 cm^2. As indicated in the images below, the soundings of interest tended to form horizontally across the pier. Horizontal cracks appear to be correlated with the identified areas.

Figure 16. Zone 1, Potential Delamination

Figure 17. Zone 2, Potential Delamination

Since the two surveys took place five months apart over summer months, minimal changes were identified on the structure. However, analysis of the April 2024 and October 2024 data revealed an increase in the size of a spall in one area, which can be visualized using AUTOSPEX™'s change detection function. This may have been the result of freeze-thaw cycles, concrete expansion during the summer months, or another factor. An example of that change is shown below:

Figure 18. Example of Change Detection Found on Rideau River Bridge

5. Limitations and Considerations

While digital technologies offer clear benefits in safety, efficiency, and accuracy, there are some limitations when compared to traditional bridge condition assessments. For instance, while not experienced during this project, surface accessibility can still be a challenge on some bridges. Bridges with heavy obstructions, overhangs, or a high density of utilities may be challenging for camera systems to access. Furthermore, traditional inspections can clean the bridge surface of vegetation, mud, and other obstructions during the inspection, whereas digital inspections do not currently have that capability.

Another potential issue is environmental factors. Again, while not experienced during this project, environmental factors such as weather, lighting, dirt, or vegetation can reduce image quality and affect detection accuracy. In some cases, data collection may be delayed altogether if snow or significant rain/thunderstorms are impacting the field work. For structures with multiple surveys, changes in environmental factors could contribute to lighting differences, vegetation growth, and other obstructions which may impact the ability to identify changes in some locations.

Finally, while the methodologies discussed here are a useful preliminary condition assessment to identify areas with visual damage and delamination, concrete coring, ground penetrating radar, and other systems may be needed to obtain additional structural data to inform a structural analysis. However, the technology discussed in this paper can be an excellent tool to inform additional investigations and data collection efforts, as needed.

6. Conclusions

The Rideau River Railway Bridge surveys in 2024 illustrate how digital condition assessments with AI-assisted defect mapping can enhance infrastructure asset management. Digital technology enables subject matter experts and various stakeholders to remotely access detailed inspection data, eliminating the need for them to physically travel to site. Through high-resolution imaging, 3D models, and AI-driven defect detection, the platform creates a digital replica of the asset that captures both the visual condition and precise measurements.

This digital environment allows engineers and specialists to analyze cracks, spalls, and other structural issues from anywhere, collaborating on assessments as if they were on site. By bringing the site to the expert, Niricson not only reduces travel costs and safety risks but also accelerates decision-making and enables more efficient allocation of expertise across multiple projects. This can be particularly useful for rural sites undergoing construction, major rehabilitations, significant maintenance, and warranty repairs that may have multiple consultants, contractors, and other stakeholders involved.

For the right project, the data generated from this type of survey could be used in the following ways:

- Design Maintenance Plans: The quantitative data generated through this study facilitates the design of meticulous and data-driven maintenance plans. These plans are essential for ensuring the safety of critical infrastructure assets.
- Conduct Preventive/Predictive Maintenance: When deployed on a structure over time, this technology enables the implementation of preventive and predictive maintenance strategies. By tracking changes in asset condition repairs, engineers can understand how and where their assets are changing, helping them to proactively address issues, reducing the need for costly reactive repairs, and minimizing service disruptions.
- Prioritize Rehabilitation/Maintenance Budgets: Understanding which assets are deteriorating most rapidly across a portfolio is paramount to allocating rehabilitation and maintenance budgets effectively. By applying this technology across the asset inventory, deterioration rates for assets can be obtained to understand which structures are deteriorating fastest and where asset owners need to spend their limited maintenance rehabilitation dollars to mitigate risks.

As digital condition assessments for bridge infrastructure become more commonplace, this project represents a step toward digitizing infrastructure portfolios. Scaling these methods across multiple bridges could enable consistent monitoring, improved safety, optimized budget allocation, and extended asset service life. Further research on network-wide implementation of this technology would be needed to understand the cost-benefit of deploying it periodically to track asset deterioration. Additionally, research on stakeholder experience with digital technologies for major rehabilitations would be beneficial to understand additional efficiencies and benefits from multi-stakeholder knowledge-sharing.