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Eye in the sky: condition monitoring of transportation infrastructure using drones

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A study was undertaken into using unmanned aerial vehicles or drones to inspect the condition of a range of transport infrastructure. A road intersection, bridge and railway crossing in the USA were each inspected using two different types of drone. Machine-learning-based feature-identification techniques, developed in an earlier case study of a car parking lot, were then used to extract information automatically from the remotely captured photogrammetric data for each asset. The findings and analysis results will help to optimise future transportation infrastructure health monitoring using unmanned aerial vehicles.

Keywords: bridges/machine learning/neural networks/pavements & roads/photogrammetry/transportation infrastructure/UAVs

1. Introduction

Much of the world's transport infrastructure is in poor condition because of the growing wear and tear caused by increased traffic and environmental loads. For example, the American Society of Civil Engineers' *2021 Report Card for America's Infrastructure* (ASCE, 2021) provided an overall grade for the nation's infrastructure of C–, which indicates a mediocre condition. Good-quality infrastructure is essential to meet a nation's basic social and economic needs, and its optimal performance is critical to national growth and productivity.

Infrastructure monitoring can be undertaken using field instrumentation and increasingly advanced land survey equipment. However, considering the human resources required and budgetary constraints, they are not conducive to proactive monitoring of infrastructure assets. As a result, asset owners and agencies may conduct reactive maintenance, which is more cost-intensive than preventive maintenance (Frangopol and Liu, 2007). This underlines the need to adopt new technologies to monitor the health of infrastructure and to develop a comprehensive plan for identifying and mitigating potential problems by preventive maintenance strategies.

Close-range photogrammetry combined with unmanned aerial vehicles systems (UAVs, UASs or drones), due to their ability to access hard-to-reach areas, offers a solution, along with navigable three-dimensional (3D) models and high-quality visuals to augment current routine inspection practices (Congress *et al*., 2018, 2022c; Fernández-Hernandez *et al*., 2015; Mikhail *et al*., 2001).

1.1 Photogrammetry

Photogrammetry is a remote data-collection technique that can record or capture information, using imaging sensors to make measurements without coming in direct contact with the inspected element (Colomina and Molina, 2014; Gonçalves and Henriques, 2015; Honkavaara *et al*., 2009; McGlone *et al*., 2004; Mikhail *et al*., 2001; Nikolakopoulos *et al*., 2017; Puppala and Congress, 2019; Puppala *et al*., 2018). It is also referred to as the art, science and technology designed to obtain reliable information about physical objects and their surrounding environment through the process of recording, measuring and interpreting patterns.

Close-range photogrammetry (CRP) using UAVs offers a broad scope of possibilities for conducting remote inspections and assessments at a micro level. Some of the important terms include flight altitude, flight lines, waypoints, ground sampling distance (GSD), overlap, ground control points, focal length, aperture, shutter speed and International Organization for Standardization (ISO) sensitivity. There is no single set of predefined settings that can be applied for all infrastructure cases and situations as they are unique for different conditions. They need to be considered based on the pilot's experience, desired data quality and inspection objectives.

Building 3D models from overlapping images is one of the most common applications of CRP technology. In this study, UAV-CRP technology was used for conducting infrastructure inspections.

1.2 Unmanned aerial vehicles

Modern image-capturing equipment has provided the impetus for conducting real-time mapping, surveying and monitoring of infrastructure assets. UAVs are increasingly used for inspection and monitoring in civil engineering. Multi-rotor, fixed-wing and vertical take-off and landing UAVs are all currently used in field operations. Dense point-cloud models, orthomosaics, digital surface models (DSMs) and contours are some of the common mapping outputs derived from aerial imagery using CRP analyses and techniques for remotely monitoring the condition of the structures.

The ability to monitor and detect physical features of infrastructure remotely is of great value to civil engineers. Due to their versatile nature, UAVs have become a popular means for remotely gathering information and assessing transportation infrastructure assets. Studies have been undertaken into using UAVs for bridge inspections, asset inventories, building monitoring,

Table 1. Details of unmanned aerial vehicles used in this study

Drone make/ model	Approximate cost with accessories: US$	Take-off weight: kg	Flight time per battery set: min	Camera sensors	GNSS geotagging	Operating temperature range	Operating frequencies: GHz
Aibot X6 hexacopter	40 000	6.6	12–15	Sony Alpha 6000 (global shutter)	Yes	–20° to 40° C	2.48 and 5.85
DJI Phantom 4 series (non-RTK)	1500–2500	1.4	24–26	In-built optical camera (global shutter)	No	0° to 40°C	2.48 and 5.85

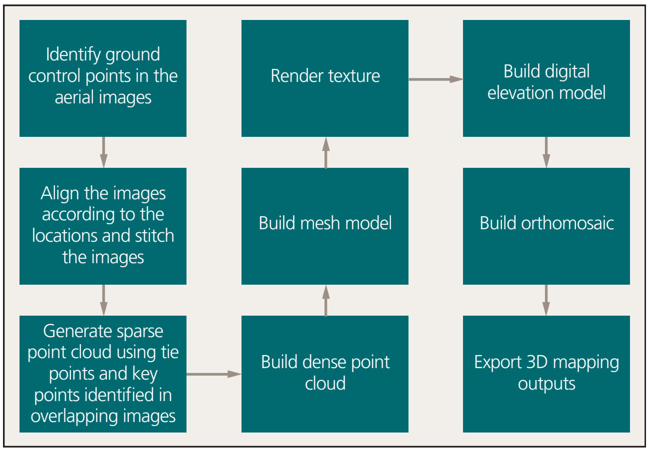

Figure 1. Typical photogrammetric data processing workflow

pre-construction surveys, construction monitoring, automated asphalt pavement inspections, traffic monitoring, law enforcement, avalanche monitoring, rail corridor monitoring, airport monitoring, stability analysis, virtual and augmented reality and disaster response (Agapiou, 2020; Carter *et al*., 2018; Congress *et al*., 2018, 2019, 2020, 2021, 2022c; Jefferies *et al*., 2022; Metni and Hamel, 2007; Moreu and Taha, 2018; Siebert and Teizer, 2014; Wang, 2017; Yinhuai *et al*., 2022; Yu *et al*., 2018).

Despite such studies, infrastructure agencies need skilled personnel for operating the UAVs, collecting and processing the data. Some agencies are collaborating with universities and industry partners in identifying potential application areas and training their personnel (Puppala and Congress, 2021). Dissemination of UAV applications for structural health monitoring of infrastructure assets is expected to bridge this knowledge gap.

This research study presents information based on hands-on experience in collecting and processing aerial imagery and analysing the 3D models of various infrastructure assets. UAVs mounted with optical sensors were used to collect aerial images of multiple transportation infrastructure assets. These images were processed and used to conduct qualitative inspections. Further, CRP techniques were used to build 3D models for conducting quantitative inspections.

Subsequently, a case study is used to show the need for and feasibility of using machine-learning-based feature-extraction techniques to obtain infrastructure asset information. The study concludes with salient observations on the advantages and limitations of these platforms to guide transportation infrastructure agencies.

2. Using UAVs for infrastructure condition assessments

The enormous number of activities needed to maintain current infrastructure assets and meet future needs requires robust and cost-effective infrastructure monitoring. The authors demonstrated aerial inspections on multiple transportation infrastructure assets in the USA. The lessons learned during some of those missions and analyses have been compiled in this paper to provide much-needed guidance to infrastructure agencies on efficient and effective health-monitoring strategies.

Two different types of drones mounted with optical sensors were used in this study to meet the inspection objectives of the three different infrastructure assets (Table 1). Both types of drones had light-emitting diode (LED) lights to assist in identifying the orientation while flying, two landing legs, a high-definition video downlink that relayed the video signals to a digital live video display unit, a camera-triggering mechanism and obstacle sensors.

An Aibot X6 hexacopter, an industrial-grade drone that could accommodate sensors on both upward and downward gimbals, was used to map the road, bridge and rail assets discussed in the current study. An integrated global navigation satellite system (GNSS) unit provided accurate geotagging data for processing the images by communicating with a laptop connected to the nearest base station through the GNSS Networked Transport of Radio Technical Commission for Maritime Services via Internet Protocol (NTRIP) caster manager. This allowed for both real-time kinematic (RTK) and post-processed kinematic (PPK) GNSS geotagging of the collected images.

A DJI Phantom 4 Pro Version 2, a low-cost quadrotor UAV equipped with an optical camera mounted on a three-axis stabilised gimbal, was used to augment the inspections. It was equipped with forward, backward and downward vision systems, and side infrared sensors, which were very useful in avoiding collisions while conducting close inspections of structures.

After identifying the mapping location of each of the three assets being inspected, the next step was to check the airspace class to determine whether there was a need to obtain a Federal Aviation Administration (FAA) airspace authorisation or waiver. The flight missions in this study were conducted in compliance with the FAA part 107 rules for the use of commercial UAVs, and the flight plans were prepared in such a way to avoid flying over people or moving vehicles, thereby eliminating the need for waivers.

The second step was to conduct a site reconnaissance of the three locations based on the information available on the internet. Preliminary flight plans were made in the office to be efficient in the

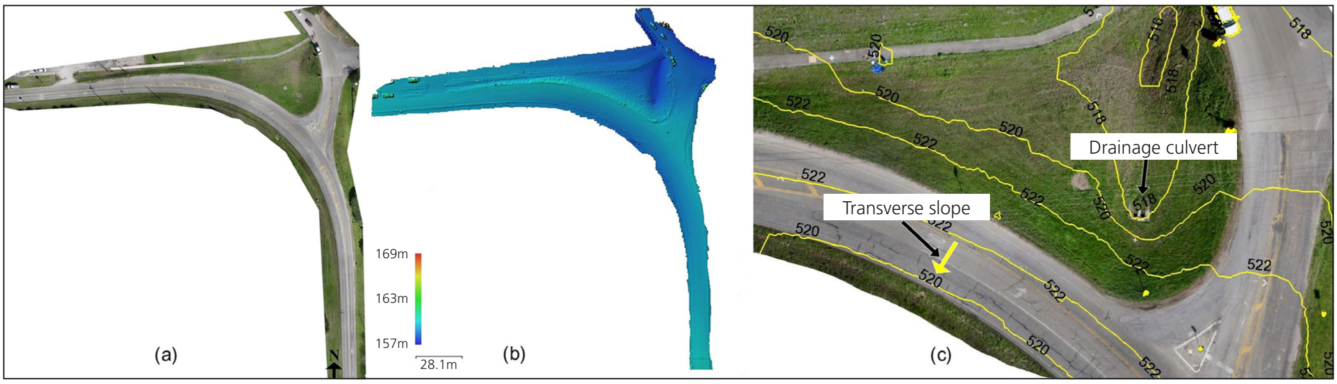

Figure 2. Aerial mapping of road intersection: (a) orthomosaic, (b) DSM, (c) 2 ft (610 mm) contours

field. All data-collection tasks were conducted by an FAA-certified drone remote pilot in command (RPIC). The complexity of the inspection determined the number of visual observers (VOs) that were used in each infrastructure asset inspected.

Safety briefings, field reconnaissance, equipment set-up, mission flights and debriefings at the site were important steps of the field inspections. Field reconnaissance, conducted before the flights, was crucial for accounting for any unfavourable conditions that were not identified during online reconnaissance and for amending flight plans. Ground control points were used in building the model and checkpoints were laid out within the inspection areas to check the models' accuracy.

Typical photogrammetric data processing and 3D model generation workflow (Figure 1) included the following steps.

- Ground control points were identified and marked in the corresponding images.
- All images were aligned and stitched to generate tie points and key points that were later used to produce a dense point-cloud model.
- The dense point-cloud model was used to generate a mesh model, and the texture was derived from the images.
- A DSM was developed from the dense point cloud.
- An orthomosaic was generated by projecting the images on either a DSM or a mesh surface.
- The 3D mapping products generated from the above workflow were exported.

3. Highway intersection

Many previous studies have been conducted by the authors to identify the condition and design characteristics of road pavements using UAV-CRP technology. For example, a stretch of road, prone to heaving due to high-sulfate soils, was aerially inspected after its rehabilitation. The rehabilitation was based on a comprehensive laboratory study to evaluate the effect of mellowing on reducing sulfate heave (Congress *et al*., 2018).

In another study, the depth and area of distress were obtained from 3D models developed from aerial imagery of a section flooded by a hurricane in Texas, USA (Congress *et al*., 2019). A cracked area was identified based on artificial intelligence and machine-learning techniques. Design characteristics such as cross-slope and longitudinal elevation profiles were obtained by collecting oblique images at different altitudes and overlaps. During data collection, traffic on the high-speed road was not interrupted as the drone was flown at a safe distance away and with the camera facing toward the pavement (Congress and Puppala, 2020).

In the current study, the authors mapped a highway intersection to assess its condition. The total flight time for inspecting the road intersection was approximately 17 min, spanning three flights. The flights were conducted at multiple altitudes with the camera viewing the pavement in nadir and oblique angles to avoid flying directly over traffic and to get data with the required resolution. The flight crew relocated to a second location at the end of the first two flights to maintain the line of sight of the drone during the third flight. At the end of field operations, a quick quality check of images was performed before generating a model with low-quality settings to ensure proper mapping of the area of interest.

The images were geotagged using satellite constellation data received by the GNSS module mounted on the drone. The images were processed to generate high-quality 3D models. The global accuracy of the model was measured as the average root mean square error (RMSE) of the checkpoint coordinates in the X, Y and Z directions, which were found to be 9 mm, 18 mm and 6 mm, respectively.

Different data outputs developed from the optical imagery are shown in Figure 2. The orthomosaic and DSM of the intersection area are shown in Figures 2(a) and 2(b), respectively. By comparing the orthomosaic and DSM, the drainage path leading to the drainage culvert could be roughly estimated from the low-elevation areas surrounding it. Contours at 610 mm intervals were laid on the intersection to provide details about the transverse slope and the drainage profile of the intersection area (Figure 2(c)).

Over its service life, the design characteristics of a pavement tend to deteriorate, leading to unsafe conditions. Hence, proactive monitoring of the pavement conditions is necessary. The transverse slope provided insight into whether the design superelevation remained intact after many years of service. The elevation profile at the central portion of the intersection was useful in considering the drainage path and planning future design improvements for the intersection.

A cost−benefit analysis conducted on using UAVs for mapping the intersection indicated that approximately 50% savings in time and cost could be realised with this method when compared to traditional methods (Puppala and Congress, 2021).

Table 2. Comparison between UAV-CRP data measurements and ground truth measurements

Marker number	UAV-CRP data measurements: mm	Ground truth measurements: mm	Absolute error: %
1	105.6	108.0	2.2
2	89.4	88.5	1.0
3	84.9	85.0	0.1
4	96.8	97.0	0.2
5	95.6	96.0	0.4
6	88.7	89.0	0.3
7	80.5	80.0	0.6

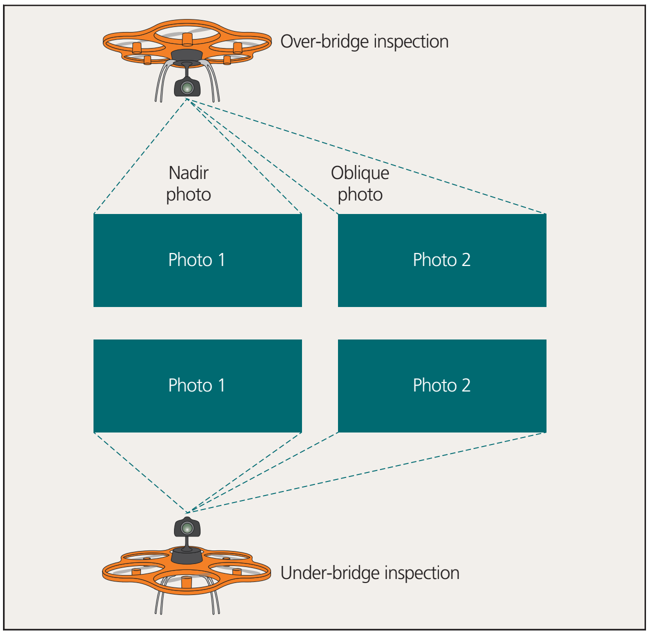

Figure 3. UAV configurations used for bridge superstructure and substructure inspections

4. Highway bridge

An aerial inspection was carried out on a newly constructed bridge, not yet opened for traffic, to explore the capabilities of UAV data collection in identifying features on bridge structures. The super- and sub-structure elements of the 213 m long and 6 m tall bridge were inspected using an optical camera mounted on the bottom and top gimbals, respectively, of the drone in separate flight missions (Figure 3).

Before every flight, the drone's compass was aligned properly by placing it in an area without any interference from nearby metal objects. For this study, the take-off operation was performed on a wooden plank laid on the adjacent grass area to reduce the magnetic interference of the reinforcement of the infrastructure asset on the drone's compass. No problems were encountered while flying close to the reinforced elements of the bridge and, despite the wind gusts, the servo gimbal provided a stable platform and helped rotate the camera in any of the three axes to map and inspect the condition of the elements. The bridge deck and the sides were inspected using a camera mounted on the bottom gimbal. While conducting the under-bridge inspections, mounting the camera on the top gimbal was observed to provide the best angle to inspect the elements of interest (Congress *et al.*, 2022b).

Since this was a newly constructed bridge at the time of data collection, tape markers with known dimensions were randomly

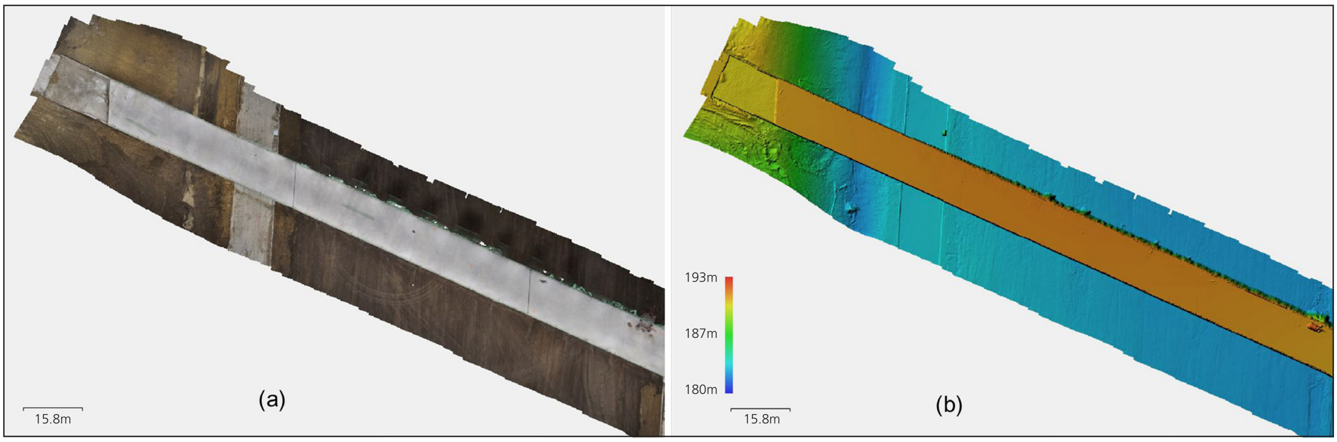

Figure 4. Aerial mapping of a bridge deck: (a) orthomosaic, (b) DSM

distributed on the bridge deck to validate the accuracy of the 3D models. A lawnmower pattern was followed while collecting the images of the surface and underneath areas of the bridge deck in different flight missions. The images were captured with a minimum overlap of 80%. Although the weather was cloudy, it did not adversely affect the quality of the data and models.

The bridge deck images were processed using ground control points to obtain 3D models and the orthomosaic shown in Figure 4. The accuracy of the model was measured as the average RMSE of the checkpoint coordinates in X, Y and Z directions, which were found to be 27 mm, 12 mm and 70 mm, respectively. This gives an idea about the global accuracy. However, the taped markers were measured manually to estimate the relative accuracy within the model and also to evaluate the resolving power of the 3D mapping products in identifying features on a concrete bridge deck.

Seven locations on the bridge superstructure were randomly marked with black tape to evaluate the performance of the UAV-CRP technology measurements (Figure 5). The scaled image generated from the aerial imagery shows the measurement of tape marker 7 (Figure 5(b)). Seven tape markers were measured and compared using UAV-CRP and traditional methods, as shown in Table 2.

UAV-CRP technology demonstrated a high degree of efficiency and accuracy while rapidly collecting the data for monitoring the bridge. The maximum error of 2.2% and an average error of less than 0.7% showed the feasibility of using UAVs as a supplemental data-collection tool to assist current traditional bridge inspection methods.

It is important to note that the lack of GNSS assistance combined with high wind gusts during the under-bridge inspection made the conditions challenging for the UAV flight. However, maintaining the line of sight, obstacle sensors and operating at a minimum offset distance of 1.8 m from the nearest obstacle ensured that aerial images of hard-to-reach areas could be collected safely. The frames extracted from the videos collected during the under-bridge inspection were processed further to identify specific features.

Since it was a newly constructed bridge at the time of inspection, there was no distress identified during the inspections. However, the surface dark paint marks formed during the construction, highlighted in red in Figure 6(a), and the borders of the panels could be quickly identified in the images processed with colour-inversion techniques (Figure 6(b)). Moisture staining could also be identified in the processed image, as the concrete background, which was relatively light in colour, helped to highlight the darker areas (Figure 6). This approach also affirmed the ability to identify cracks on concrete surfaces using drone imagery and offered a quick method for identifying cracks or efflorescence staining that commonly forms on in-service bridges.

The information captured by the UAV inspections could be an important part of efficient asset management as it can be used to build a 'reality twin' model of the bridge showing existing conditions of the structure (Dang and Shim, 2020). This information can be fed into a digital twin, which is a digital replica of any physical asset, process or system, with the help of artificial intelligence, machine learning and/or data analytics to create live digital models. The digital twins can learn and update from several data sources to represent and predict the current and future condition of their physical counterparts (Lu *et al*., 2022).

Information captured by the UAV inspections could be an important part of efficient asset management

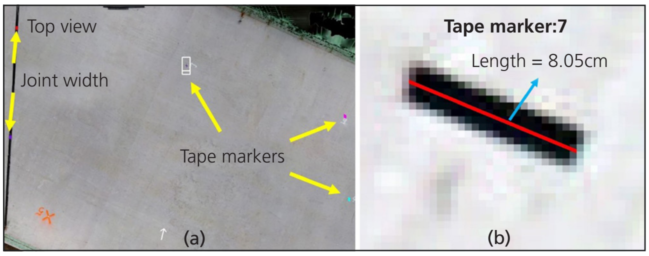

Figure 5. Bridge deck inspection: (a) locations of a few markers, (b) pixel view of tape marker 7 on scaled image from UAV-CRP technology

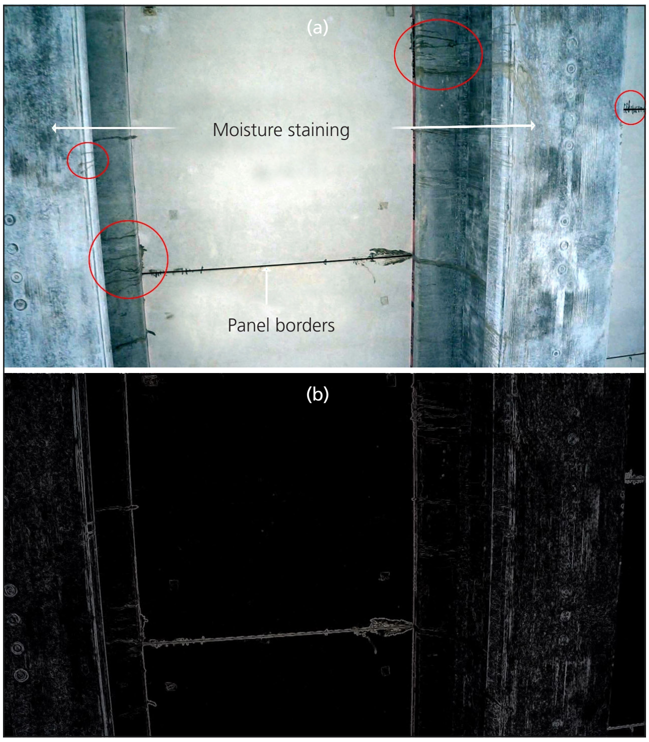

Figure 6. Under-bridge aerial inspection: (a) optical image, (b) colour inversion

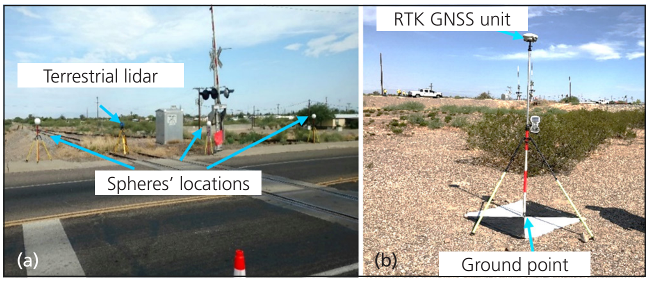

Figure 7. Rail crossing mapping: (a) terrestrial lidar scanning, (b) collecting ground point information using an RTK GNSS unit

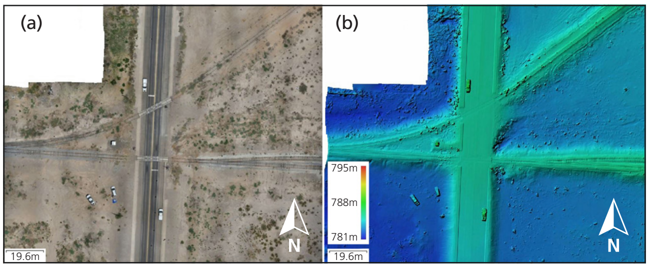

Figure 8. Aerial inspection of rail crossing: (a) orthomosaic, (b) DSM

This analysis indicated that the UAV-CRP data can accurately detect several features of a rail corridor efficiently

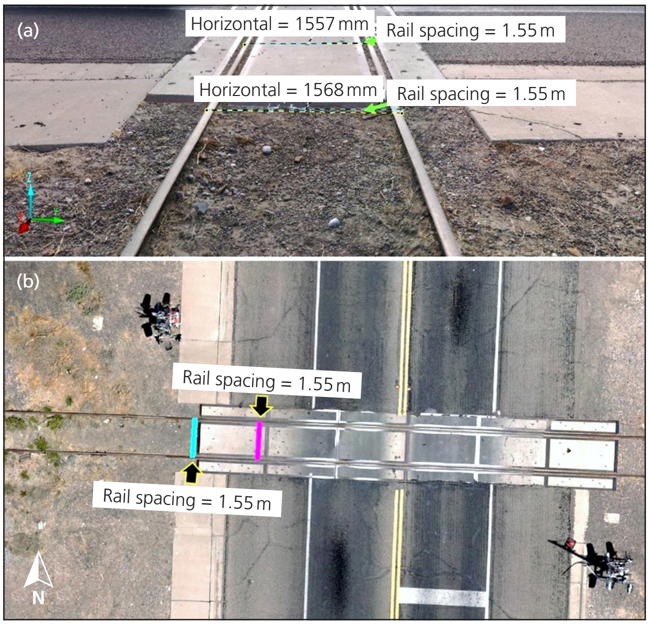

Figure 9. Rail spacing measured from rail crossing data collected using (a) terrestrial lidar, (b) UAV-CRP technology

5. Rail crossing

An at-grade highway crossing of a railway was mapped using terrestrial lidar (Figure 7(a)) and UAV-CRP technology to evaluate safety. Ground-point information was also collected using a ground RTK GNSS unit shown in Figure 7(b). UAV flights were planned to collect the images with 80% overlap. Aerial imagery was collected in two 10 min flights. The images were geotagged and processed to obtain the dense point-cloud model, orthomosaic and DSM of the crossing area. The orthomosaic and DSM offered an overview of the elevation profile of the area, read from the colour-coded elevation bar, as shown in Figure 8(b).

The average RMSE of the model in the X, Y and Z directions was measured as 24 mm, 52 mm and 14 mm, respectively. This provided an idea about the error in global location, but terrestrial lidar measurements provided a better idea about the accuracy of the 3D model. 'Ground truth' measurements were collected using terrestrial lidar scanning. Traffic flow was mostly unobstructed and was only regulated while the two 15 min terrestrial lidar scan surveys were being conducted to map the crossing area. A terrestrial lidar with a resolution of 1/4 and quality of 4× was used to obtain the desired level of detail. Four spheres, three on one side and one on the other side of the intersection along the rail line, were placed to assist in stitching the two lidar scans.

The measurements obtained from the terrestrial lidar and the UAV-CRP data were compared to evaluate the accuracy of the aerially mapped data. The spacing between the two rails was measured at two locations from the data collected using terrestrial lidar and UAV-CRP technologies, as shown in Figures 9(a) and 9(b), respectively. The nearest and farthest rail spacing measurements in the lidar data are represented by the blue and pink lines in the UAV-CRP data, respectively, shown in Figure 9(b).

Considering the terrestrial lidar data as the benchmark, the percentage error in the two spacings measured from the UAV-CRP data was obtained as 0.7% and 0.3%, respectively. This analysis indicated that the UAV-CRP data can accurately detect several features of a rail corridor efficiently. With this assurance of accuracy, the rail corridor data models were analysed further to evaluate their safety. Congress *et al*. (2020) pioneered a study using UAV-CRP data to evaluate the safety of rail crossings, and they were successful in identifying obstructions within the line of sight of drivers negotiating the crossings.

Congress and Puppala (2021) provided a comparison of the real-field view and model view of an obstruction generated from

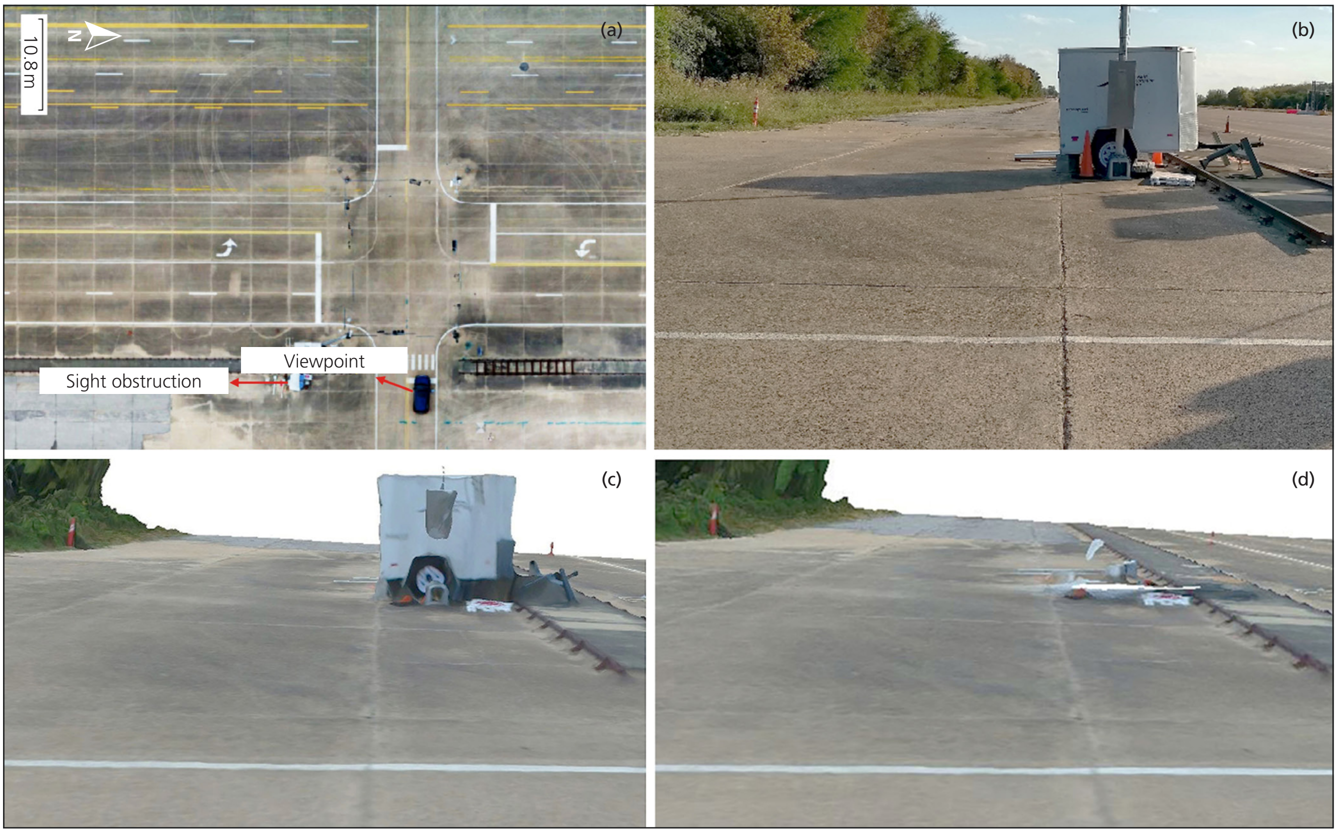

Figure 10. Obstruction analysis at test rail crossing area: (a) orthomosaic, (b) real view – driver's eye level, (c) digital view – driver's eye level, (d) digital view – after obstruction removal

the unmanned aerial images captured at a test rail crossing site (Figure 10). They also highlighted the unique ability of UAV-CRP technology to provide views at different locations that could not be obtained from traditional data-collection methods without stopping traffic for a significant amount of time. Based on the observations made in the digital replica of the rail crossing developed from the UAV-CRP data, appropriate planning could be made to displace or remove the obstruction, as shown in Figure 10(d).

6. Machine-learning-based feature-identification in aerial data sets

The aerial imagery collected using UAVs can be used to make either qualitative and/or quantitative assessments of infrastructure assets. Qualitative assessments can be performed using either the raw images or the 3D models generated from the aerial images. Quantitative assessments can be performed using the 3D models generated from aerial imagery. Redundancy in the data collected helps in building high-quality data models and making accurate assessments. These assessments are observed to be effective when compared to conventional inspection practices. However, manually analysing the raw imagery and/or 3D models representing vast

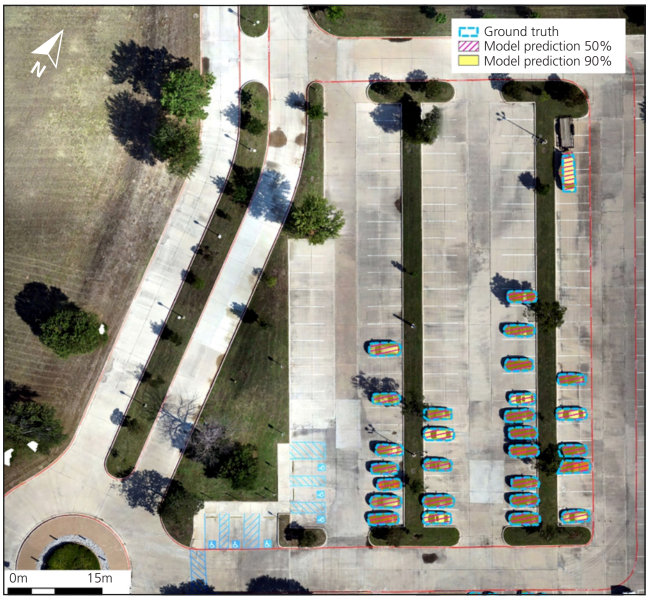

Figure 11. Neural-network-based prediction of cars at 50% and 90% confidence scores

areas of infrastructure assets is still laborious (Congress *et al*., 2022a). The authors demonstrated the use of machine-learning-based algorithms to identify the features in a case study.

In the case study, a geo-referenced orthomosaic generated from aerial imagery and 3D models was analysed using machine-learning-based instance-segmentation techniques. One of the key advantages of coupling machine learning with photogrammetric techniques is that the 3D mapping products offer scaled views and the location of the infrastructure asset, which can be used to feed the infrastructure condition information directly to the network-level asset management database. The area covered by the object class, detected by the mask, can be measured by using pixel resolution and tagged to its global location.

A neural network model was trained to identify cars and performed inferencing on an orthomosaic of a car park, as shown in Figure 11. The inference was conducted at confidence levels of 50% and 90% to evaluate the performance of the model. Adopting a higher confidence level for inferencing ignores the detection of doubtful object classes and vice versa. Depending on the model performance, there can be potential false negatives with a higher confidence level and potential false positives with a lower confidence level. Hence, an appropriate image resolution and confidence level need to be selected for training and inferencing, respectively (Congress *et al*., 2022a).

In Figure 11, the model with both 50% and 90% confidence levels automatically detected all the cars. The locations of the cars identified by the neural network model were extracted from the geo-referenced orthomosaic and fed into a geographic information system (GIS) database.

It can be observed that multiple cars in the car parking lot were not only identified but their location coordinates were tagged to the global coordinate system and automatically fed into a GIS-based system. This reduces a lot of manual labour for identifying different features, if it were to be performed by a person, and helps in dedicating human resources toward other important applications.

Although they reduce manual labour, these technologies are not expected to replace people in the near future as they require human input when they encounter situations or features that were not provided during the training of the model. An unfamiliar situation or feature might happen frequently in a field like civil engineering as the environmental, lighting and background conditions of objects can change dynamically and present the same object with a different appearance. Hence, a balance between human involvement and machine analysis needs to be obtained based on the complexity of the problem being addressed.

The case study discussed in this section highlights the need for and feasibility of adopting machine-learning-based techniques to augment the aerial imagery and derived data sets depicting the infrastructure conditions. This can also help in the automatic identification and tracking of parking usage over time using the same flight paths and plans. Similar approaches can be used to automatically detect various infrastructure features and distress in large data sets and feed them to the asset management database.

7. Summary and conclusions

Proactively monitoring the health of infrastructure assets will facilitate preventive maintenance. The multiple views of infrastructure offered by the immersive visualisation of the models derived from UAV-CRP technology can help to identify the condition of road pavements, bridges and railway assets, as demonstrated by the three examples in this study. Moreover, subjective inspections can be transformed into objective nature with the help of various image-analysis techniques.

Aerial data collection facilitates efficient inspection of long and linear infrastructure assets. It also helps access hard-to-reach areas and derive the design characteristics and health condition of infrastructure efficiently and cost-effectively. The same aerial data sets can be used to obtain multiple attributes of an infrastructure asset.

For road pavement inspections, distress, design features and construction practices can be monitored using UAV-based data collection. Moreover, blind spots to traffic can be identified quickly from the 3D models without interrupting traffic for long periods during data collection.

For bridge inspections, UAVs provide access to hard-to-reach areas and facilitate 360° bridge inspections. An increase in the frequency of high-intensity weather events and aging bridge infrastructure require the adoption of UAVs to efficiently conduct a preliminary inspection of bridges.

For rail inspections, UAVs are being used to monitor tie conditions, washout, rail buckling and other surface conditions of a rail track. The 3D models are also being used to identify humped crossings and trespassing of an at-grade road crossing. Moreover, machine-learning tools are being leveraged to analyse these aerial data sets and extract information for infrastructure health monitoring. Although object-detection techniques offer faster detection results, instance-segmentation techniques were observed to be better for civil engineering assets due to their cluttered background.

Similar to any technology, UAV-CRP technology also has some limitations. An optical camera mounted on a UAV can only provide the surface condition of an infrastructure element. It cannot provide penetrative information, and will not provide any information if there is an object obstructing its view. Loss of Global Positioning System (GPS) connection and poor lighting conditions are some of the challenges for operating and collecting under-bridge data. Finally, data storage may also cause an issue if proper data-management strategies are not followed.

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