Uncrewed Aerial Vehicles in Bridge Inspection

Subjects: Engineering, Civil Contributor: Zahra Ameli, Yugandhar Aremanda, Wilhelm Friess, Eric Landis

Uncrewed Aerial Vehicles (UAV) constitute a rapidly evolving technology field that is becoming more accessible and capable of supplementing, expanding, and even replacing some traditionally manual bridge inspections. Given the classification of the bridge inspection types as initial, routine, in-depth, damage, special, and fracture critical members, specific UAV mission requirements can be developed, and their suitability for UAV application examined.

Keywords: bridge inspection ; UAV ; Payload ; Flight time ; Remote sensing ; Crack detection ; Optimization

1. Types of Bridge Inspection

According to the National Bridge Inspection Standards (NBIS, 2004), there are eight types of bridge inspection: inventory, routine, damage, in-depth, fracture critical member, hands-on, special, and underwater inspection ^[1]. A summary of the inspection types and their scope and mission is presented in **Table 1**.

Inspection Type	Scope and Mission
Initial (inventory)	Provide all Structure Inventory and Appraisal (SI&A) data and determine baseline structural conditions and load capacity ratings • 3D model construction
Routine	 Evaluate physical and functional condition of structure and ensure that service requirements are satisfied Defect detection 3D model reconstruction
In-depth	 Hands-on inspection to determine deficiencies not detectable by routine inspection Fatigue crack detection Surface crack detection Corrosion detection
Damage	 Determine if a bridge requires load restrictions or closures or the extent of repair required. Surface crack detection Fatigue crack detection
Special	 Intended to monitor a known or suspected deficiency at a specific location Surface crack detection Fatigue crack detection Corrosion detection

Table 1. Bridge inspection types and scope.

Inspection Type	Scope and Mission
Fracture critical member	 A detailed hands-on inspection to detect cracks. Surface crack detection Fatigue crack detection

As is shown in Table 1, an initial (inventory) inspection is a preliminary inspection performed prior to entering service to determine baseline structural conditions. It is a fully documented investigation and is accompanied by load capacity ratings. Routine inspection is the most common type of inspection, and for almost all bridges, it is required by FHWA at regular intervals of less than 24 months so that inspectors can monitor defects and deterioration. Routine inspections evaluate the physical and functional condition of the structure, including all elements of the bridge superstructure, deck underside, and substructure that are accessible from the ground ^[2]. During routine inspections, a qualified bridge inspector records the degree of damage for each bridge element, following an element numbering system and a checklist. In-depth inspection is a close-up inspection of one or more structural members to detect any deficiencies not readily visible using routine inspection procedures. This inspection may include a load rating to assess the residual capacity of the member or members, depending on the extent of the deterioration or damage. Damage inspections should be performed due to collision, fire, flood, significant environmental changes, or loss of structural support. If major damage has occurred, inspectors must evaluate fractured members, section loss, make measurements for the misalignment of members, and check for any loss of foundation support 3. Special inspections are used to monitor known or suspected deficiencies such as foundation settlement or scour, fatigue damage, or the public's use of a load posted bridge. Special inspections are usually not comprehensive enough to meet the requirements of routine inspections ^[2]. Fracture critical inspection is a hands-on (within arm's length of the component) inspection of a fracture critical member or member components. It may include visual and other nondestructive evaluation. This may require that critical areas be specially cleaned prior to the inspection and additional lighting be used.

2. Developments of UAVs in Bridge Inspection in the US

Due to rapid advancements in UAV technology in recent years, in the US, Departments of Transportations (DOTs) have shown increasing interest in the use of UAV for bridge inspections ^[4]. In 2008, California DOT (Caltrans) ^[5] and the University of California at Davis designed a custom twin-motor, single-duct UAV to be tethered to the ground, making it easier to control and conform to the FAA regulations at the time. The objective of Caltrans was to construct an "Aerobot" to easily access structural components at high altitudes, such as girders ^[6]. Caltrans terminated the project as it did not result in a fully deployable aerial vehicle due to its instability in the wind and the unsuccessful performance of an altitude holder sensor.

Wisconsin DOT \square used two different UAVs for evaluating damage conditions specific to each of the three roadway bridges, including two steel girder bridges and one steel truss bridge. They learned that quality of the UAV equipment is important for bridge inspections since the results quality is tied to the resolution of the images and the ability to view the bridge elements from proper angles. Idaho Transportation Department [B] researched the use of UAVs in under-bridge inspections for detecting fatigue cracking. The conclusion of the experiments was that detecting fatigue cracking and other bridge defects by using visual spectrum and thermal image processing is feasible, but requires a careful selection of UAS platforms, on-board avionics, and data collection sensors [9].

Michigan DOT (MDOT) ^[10] has conducted tests of UAVs for bridge inspections since April 2015. Images taken with a UAV were used to detect deficiencies in bridge decking for potholes and wear, and involved the use of RGB cameras and infrared and LiDAR sensors. The studies demonstrated that using UAV increases safety and reduces inspection costs. It was also found that simultaneous use of different sensors can significantly improve the accuracy of collected data. Oregon DOT (ODOT) ^[11] conducted a statewide study on UAV applications for bridge inspections. Wind condition was found to be the most important environmental variable in operating UAV close to bridges, while ambient light conditions and camera settings are critical to obtaining high-quality imagery. The ability to articulate a camera in any direction with a zoom lens and employ an onboard camera-assistant spotlight was the most useful technical feature for collecting visual data. The use of a UAV was most effective for initial and routine inspections and less effective for more complex in-depth inspections that require touching, probing, or scraping a bridge.

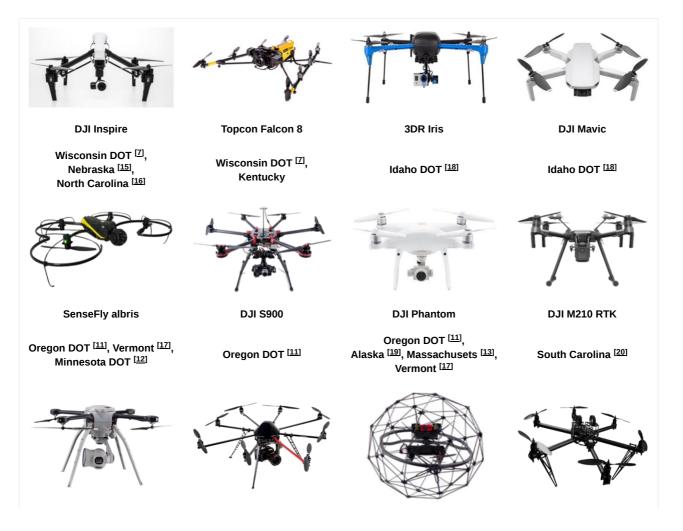
Minnesota DOT (MnDOT) ^[12] performed one of the most comprehensive studies evaluating UAVs' application and effectiveness in bridge inspections. In the first phase (2015), the research team learned that UAVs capable of pointing

cameras upward and operating without GPS have better performance for bridge inspection applications. In the second phase (2017), the research team expanded the demonstration to different structure types and sizes using a SenseFly Albris UAV. They concluded that this vehicle is flexible to control, and its operational capabilities are not diminished by the loss of GPS signals. In the third phase (2018), 39 bridges including a wide range of sizes, types, and locations are inspected using SenseFly Albris and Flyability Elios UAVs (a quadcopter enclosed in a spherical wireframe cage to avoid collision damage/specialized in performing indoor inspections by utilizing computer vision-based navigation). They learned that easy piloting, access to confined areas, and cost-effectiveness are the benefits, whereas short battery life, video interference due to the cage and air flow, and debris are the limitations of this specific type of drone. It was also found that UAV platforms equipped with thermal sensors can effectively detect concrete delamination. The study recommended using UAV for routine inspections where hands-on inspection is not required. Another recommendation relates to the use of UAV equipped with sophisticated collision avoidance systems as well as the use of collision-tolerant platforms which can operate in direct contact with the bridge structure.

UMass research team ^[13] developed and tested practical procedures and protocols to guide MassDOT in integrating UAV technologies into bridge inspections. It was determined that selection of the proper types of UAV platforms and sensors are the primary factors that affect the success of UAV integration into the bridge inspections. Kansas DOT (KDOT), in collaboration with the Kansas State University Transportation Center, studied the potential of UAV implementation within KDOT. They found out there is a need to handle large and overwhelming volumes of collected data ^[14]. Nebraska DOT (NDOT) conducted a study on UAV applications in bridge inspection program. The NDOT study concluded that except fracture critical bridge inspections, all other types of bridge inspections could incorporate UAV ^[15].

North Carolina DOT (NCDOT) partnered with North Carolina State University to evaluate the potential benefits of UAV for transportation applications. The conclusion of the study indicates that the major factors affecting success of UAV missions include weather, sensor capabilities, flight planning, software processing, and ground control point design and placement $^{[16]}$. Vermont Agency of Transportation (VTrans) tested UAV capabilities for bridge inspections. It was noted that significant increases in the volume of data collected with the help of UAV may create additional challenges for data storage and processing. It was also found that photogrammetry can successfully replace LiDAR in the generation of accurate 3D models for lower cost $^{[17]}$. Most common types of UAVs which state DOTs have used for bridge inspection purposes are shown in **Table 2**.

Table 2. Most frequently used UAVs within state DOTs for bridge inspection purposes.



Aeryon SkyRanger	Mikrocopter Hex	Flyability Elios	Cinestar
Minnesota DOT [12]	North Carolina ^[16]	Minnesota DOT [12]	Norht Carolina ^[16]

There are numerous ongoing research programs to eliminate current limitations and address the needs in the application of UAVs in bridge inspection. These include handling large volumes of collected data, environmental conditions affecting the quality of images, navigation and flight stability in areas with poor GPS signals and around large steel structures, collision avoidance capabilities and image processing, and advanced computational methods to detect/evaluate deck deficiencies. A few of these studies are summarized in this section.

To analyze the effectiveness of drones as supplemental bridge inspection tools and facilitate bridge inspection, researchers have conducted numerous studies. Junwon Seo et al. (2018) [21] performed an analysis of the effectiveness of drone-based bridge inspection. They used a DJI Phantom 4 guadcopter to inspect a bridge. The drone was able to identify various damage types, including cracks, spalling, corrosion, and moisture on the bridge. During the conduction of the study, some limitations were identified, including high wind speeds, camera overexposure, low illumination, and flight challenges due to obstacles in an enclosed section (e.g., between closely spaced girders). S. Sankarsrinivasan et al. [22] proposed a novel complete field mapping protocol using UAVs to enable their real-time health monitoring. This method integrates data captured by a UAV to identify cracks and assess surface degradation using grayscale thresholding. They used a custom-built hexacopter with a payload capacity of 110 g and a 20 min flight time. Yunas Zewdu Ayele (2020) [23] proposed a methodology for a UAV-based bridge inspection to assess bridge damage using novel technologies. Their methodology for bridge inspection involves collecting data and training a model which enables modifying drone flights to obtain optimum efficiency. The data gathered from the previous stage is built into 3D models to capture the element geometry of every bridge asset to use for navigational and controlling purposes. Chen et al. (2016) ^[24] developed a hexacopter with an upward gimbal that can capture upward imagery and accommodate additional attachments such as an ultrasonic sensor, laser scanner, and LiDAR. They learned that position estimation using a laser scanner can only work in the specific bridge environment, and it is still a problem without GPS when the environment is much more complex. To fly in a more complex environment, other localization methods need to be integrated into the system to get a more precise position to control the drone's flight. D. Roca et al. [25] used a Mikrokopter Okto XL octocopter for inspecting outdoor building facades. This UAV has a Kinect sensor mounted unit capable of acquiring geometric data in 3D, which can then be reproduced as a 3D model to evaluate potential damages. HekmatiAthar et al. (2020) [26] introduced a hierarchical multiple-criteria decision making framework for UAV-enabled bridge inspection selection practices. The initiated framework employed a hierarchical method to analyze 32 criteria categorized in flight performance, situational awareness, payload and sensor capabilities and communication quality.

Even with advances in UAV technology, manual piloting remains a challenge, and developing navigation and autonomous flight capabilities are of growing interest. For example, Yu et al. 2019 ^[27] presented a LiDAR-based approach for autonomous navigation using 2D LiDAR scanning. Bolourian et al. (2020) ^[28] proposed an optimized path planning technique for a UAV-based LiDAR scanner that performs bridge inspections. This technique uses genetic algorithms for solving the traveling salesman problem of potential locations of bridge cracks with an objective of minimum flight time and maximum visibility. Jung et al. 2020 ^[29] addressed a hierarchical graph-based simultaneous localization and mapping (SLAM) method for fully autonomous bridge inspection using an aerial vehicle. They concluded that even with accurate position estimation under a bridge, the risk of UAV collision significantly increases when a wind gust of over 10 m/s suddenly occurs.

The ability to convert images or video data into actionable information automatically and robustly remains challenging. Vision-based approaches, in conjunction with cameras and UAVs, offer the potential for rapid and automated inspection and monitoring for bridge condition assessment ^[30]. Sutanu Bhowmick et al. ^[31] concluded that UAVs with real-time vision sensing are more efficient in terms of time and resources. They used pixel segmentation to identify whether a particular pixel belonged to a crack or not. Krisada Chaiyasarn et al. ^[32] developed a convolutional neural network (CNN) based image crack detection method for inspecting historical structures using feature extraction. The data is captured using a DJI Phantom UAV. Saleem et al. 2020 ^[33] proposed instant crack damage detection using an image capturing and geotagging system with a CNN for automated inspection. The damages extracted by the CNN are instantly transformed into a global bridge damage map, with georeferencing data acquired using image capturing and geotagging. To overcome the limitation of visual inspection in terms of post-processing big data to develop a 3D model, a UAV-based real-time autonomous crack detection algorithm was proposed by Morgenthal et al. ^[34]. This system includes machine learning-based feature detection of target areas that provides crack information to the team instantly while capturing data.

The application of infrared thermography (IRT) techniques has been demonstrated in several research projects. Omar et al. (2017) [35] demonstrated the applicability of UAV-mounted thermal cameras for quantitative measurements of delamination in RC bridge decks. Image analysis based on the k-means clustering technique was utilized to segment the mosaic and identify objective thresholds. Mac et al. 2019 [36] considered simultaneously using the results from the handheld IR camera, and the IR camera mounted on a UAV. They found out that there is a strong correlation between the size and detectable depth of delamination. Hiasa et al. 2017 [37] presented a methodology that combines numerical modeling and IRT data to improve the usability and efficiency of data analysis, possibly leading to automated analysis and evaluation. To obtain thresholds for data processing, finite element model simulation was utilized. Washer et al. (2010) [38] presented results from a study of the effect of solar loading on the detection of embedded targets in a large concrete block. The effect of the depth of the embedded target is discussed, as well as the timing of inspection (relative to sunrise) that resulted in maximum contrast in thermal images. Ellenberg et al. 2016 [39] demonstrated the capability of UAVs equipped with both color and IR cameras to rapidly and effectively detect and estimate the size of regions where subsurface delamination exists. Shen et al. (2020) [40] suggested that IRT technology could be a complementary method to evaluate the delamination of concrete bridge decks in addition to the existing chain dragging method currently used by the Nebraska Department of Transportation (NDOT). They mentioned some common pitfalls such as dark asphalt smears on the concrete deck, wet deck surface, and excessive dirt covering the deck surface that must be avoided during the survey.

Ongoing research that addresses the limitations of GPS-based UAV navigation relies on computer vision approaches to seek and avoid obstacles and optimize the flight path. Youn et al. ^[41] created a real-time surrounding map for the UAV navigation in a GPS denied environment with the integration of an error state Kalman filter and an open-sourced SLAM (simultaneous localization and mapping) algorithm. To achieve flight control and reachability, a nonlinear observer control technique can be implemented to guide the UAV ^[42]. This system uses an onboard UAV sensor suite and a visual camera to identify a target with as low as four feature points and compare them with a preprogrammed feature data library. Based on the feature identified, the UAV takes the necessary position and velocity corrections autonomously without a pilot command ^[43]. Flightpath optimization is another major aspect of infrastructure inspection and can be achieved using novel optimization techniques, such as particle swarm optimization ^[44].

Custom-made UAVs have gained considerable attention to address the current limitations of off-the-shelf vehicles. Whitley et al. (2020) ^[45] presented a solution to the current limitations in the implementation of UAVs which are reliance on a skilled operator and/or the requirement for a UAV to operate in a cluttered, GPS-denied environment. They utilized commercial off-the-shelf hardware, including laser rangefinders, optical flow sensors, and live video telemetry. González-deSantos et al. 2020 ^[46] presented a new payload to perform contact inspection in large structures using UAV. The payload has been designed to be independent of the flight controller. The payload approaches the structure slowly and avoids bounces during the first touch. This sensor measures the thickness of metal sheets when in contact with it. Myeong et al. 2015 ^[47] demonstrated the use of wall-climbing UAVs that can fly and stick on walls to perform inspections. Kocel et al. ^[48] developed a UAV payload with a combination of a long probe and a transducer that contacts the surface and moves along with the UAV for a thorough inspection. They developed a robust flight control system to maintain minimal distance from the inspecting surface, a major requirement for this UAV technology.

3. Various Applications of UAV Mounted Sensors in Bridge Evaluation

• **Surface crack detection:** The majority of literature papers have addressed crack detection as the primary application of UAVs in bridge inspection ^[49]. The image-based surface crack assessment method consists of two main steps. The first step is crack detection, which intends to eliminate noise and extract crack objects from the images. The second step of crack assessment is the extraction of crack edges and calculating crack parameters, including crack width and length ^[50]. To detect bridge surface cracks, RGB cameras are typically used. The UAVs can capture high-quality images from hard-to-reach areas of the bridge ^{[51][49]} using optical cameras, but the distance from the structure surface, illumination condition, wind, and the minimum number of the required images are important considerations that need to be taken into account.

• **Delamination:** The horizontal debonding in the subsurface of the deck, known as deck delamination, often indicates the corrosion-induced deterioration of the deck reinforcement ^[52]. For the task of delamination profiling through thermography, the existing challenges are the shape and the depth of delamination, environmental factors such as air temperature and solar intensity, which introduces the feature variation of the same delamination, surface textures such as cracks, color difference, patching, and road painting, which adds external noise ^[53]. Image processing techniques were developed to extract temperature abnormalities automatically, quantitatively, accurately, and sensitively. This process mainly utilizes threshold temperature values and temperature gradients. The first challenge is determining threshold values because the

values are affected by environmental conditions. The second challenge is difficulty in evaluating the entire target object by one global threshold value. The reason may be that the entire surfaces of infrastructures or buildings are not under the same conditions, and each local area has a different average temperature and gradient ^[54].

• **Corrosion:** Corrosion is a natural phenomenon involving an electrochemical process liberating a positive charge that becomes a stable compound. Although some corrosion occurs on the subsurface metal materials, such as the steel reinforcement used in concrete for bridges, a large amount of corrosion happens on the surface of steel bridges ^[55]. RGB and IRT cameras are commonly used for corrosion detection ^{[56][57]}. Infrared Thermography is a promising method of corrosion detection, measurement, and mapping, but more research needs to be done to perfect this method for use in the field ^[58].

• Fatigue: Fatigue cracks are very difficult to see and may have lengths shorter than 7 mm and widths narrower than 0.1 mm. Fatigue cracks normally appear in the superstructure near large cross frames, welded stiffeners, or other complex geometries, making access difficult. To detect fatigue cracks, RGB and IRT cameras are usually used ^[8]. Careful selection of a UAV platform, environmental conditions, and lighting conditions are important factors that affect UAV-based fatigue crack detection ^[59].

• **3D model reconstruction:** To help bridge managers visualize the geometric information (e.g., damage location) and surface condition (e.g., damage type and extent) of an existing structure, **3D** models of the structures are constructed to establish a base onto which damage information can be referenced. RGB cameras and LiDAR sensors can be implemented to generate **3D** models ^[60]. In contrast to LiDAR, which usually contains more **3D** points, photogrammetry uses a collection of 2D images taken from various angles and locations around the structure to create **3D** points. Because photogrammetry matches image features to create the **3D** points, there is a significant computational expense and less accuracy than LiDAR. However, the only equipment required for photogrammetry is an optical sensor, while UAV-based LiDAR systems require expensive LiDAR sensors and GPS systems, which decreases battery life by adding additional payload to the system ^[61].

References

- 1. National Bridge Inspection Standards; Federal Highway Administration, Department of Transportation. 2004. Available online: https://www.govinfo.gov/content/pkg/FR-2004-12-14/pdf/04-27355.pdf (accessed on 1 April 2004).
- 2. Tomiczek, A.P.; Whitley, T.J.; Bridge, J.A.; Ifju, P.G. Bridge Inspections with Small Unmanned Aircraft Systems: Case Studies. J. Bridge Eng. 2019, 24, 05019003.
- 3. Dorafshan, S.; Thomas, R.J.; Coopmans, C.; Maguire, M. A Practitioner's Guide to Small Unmanned Aerial Systems for Bridge Inspection. Infrastructures 2019, 4, 72.
- 4. Jeong, E.; Seo, J.; Wacker, J. Literature Review and Technical Survey on Bridge Inspection Using Unmanned Aerial Vehicles. J. Perform. Constr. Facil. 2020, 34, 04020113.
- 5. Moller, P.S. Caltrans Bridge Inspection Aerial Robot Final Report; University of California at Davis: Davis, CA, USA, 2008; p. 33.
- Duque, L.; Seo, J.; Wacker, J. Synthesis of Unmanned Aerial Vehicle Applications for Infrastructures. J. Perform. Constr. Facil. 2018, 32, 04018046.
- 7. Baker, M. UAS Bridge Inspection Pilot; Wisconsin Department of Transportation: Madison, WI, USA, 2017.
- Dorafshan, S.; Maguire, M.; Hoffer, N.; Coopmans, C. Fatigue Crack Detection Using Unmanned Aerial Systems in Under-Bridge Inspection. 2017; undefined. Available online: https://www.semanticscholar.org/paper/Fatigue-Crack-Detection-Using-Unmanned-Aerial-in-Dorafshan-Maguire/ba0a53bb697b58f7fa8c61654b7556dfc754a290(accessed on 29 October 2021).
- 9. Plotnikov, M.; Collura, J. Integrating Unmanned Aircraft Systems into State Department of Transportation Highway Bridge Inspection Procedures: Challenges, Implications, and Lessons Learned. Transp. Res. Rec. J. Transp. Res. Board 2021, 2676, 036119812110444.
- Brooks, C.; Dobson, R.J.; Dean, D.B.; Banach, D.; Oommen, T.; Havens, T.; Ahlborn, T.; Cook, S.J.; Clover, A. Evaluating the Use of Unmanned Aerial Vehicles for Transportation Purposes: A Michigan Demonstration; Michigan Department of Transportation: Lansing, MI, USA, 2014.
- 11. Gillins, D.T.; Parrish, C.; Gillins, M.N.; Simpson, C. Eyes in the Sky: Bridge Inspections with Unmanned Aerial Vehicles; Oregon Department of Transportation: Salem, OR, USA, 2018.

- 12. Lovelace, B.; Wells, J.L. Improving the Quality of Bridge Inspections Using Unmanned Aircraft Systems (UAS); Minnesota Department of Transportation: St. Paul, MN, USA, 2018; p. 345.
- Plotnikov, M.; Ni, D.; Price, D. The Application of Unmanned Aerial Systems In Surface Transportation—Volume II-A: Development of a Pilot Program to Integrate UAS Technology to Bridge and Rail Inspections; Massachusetts Department of Transportation: Boston, MA, USA, 2019; p. 74.
- McGuire, M.; Rys, M.J.; Rys, A. A Study of How Unmanned Aircraft Systems Can Support the Kansas Department of Transportation's Efforts to Improve Efficiency, Safety, and Cost Reduction: Final Report; Kansas Department of Transportation: Manhattan, KS, USA, 2016.
- 15. Daly, M. NDOT Explores Unmanned Aerial Vehicle Bridge Inspection. The Roadrunner; Nebraska Department of Transportation: Lincoln, NE, USA, 2018.
- 16. Zajkowski, T.; Snyder, K.; Arnold, E.; Divakaran, D.; North Carolina State University. Institute for Transportation Research & Education; NextGen Air Transportation Consortium Unmanned Aircraft Systems: A New Tool for DOT Inspections: Final Report. 2016. Available online: https://rosap.ntl.bts.gov/view/dot/32892 (accessed on 22 January 2022).
- 17. O'Neill-Dunne, J. Unmanned Aircraft Systems for Transportation Decision Support; University of Vermont: Burlington, VT, USA, 2016.
- Dorafshan, S.; Maguire, M.; Hoffer, N.V.; Coopmans, C.; Thomas, R.J.; Utah State University. Department of Civil and Environmental Engineering. In Unmanned Aerial Vehicle Augmented Bridge Inspection Feasibility Study; Utah State University: Logan, UT, USA, 2017; p. 177.
- 19. Morehouse, C. Technology for Alaskan Transportation; Alaska Department of Trasportation: Fairbanks, AK, USA, 2016; p. 9.
- 20. Burgett, J.M.; Bausman, D.; Comert, G. Unmanned Aircraft Systems (UAS) Impact on Operational Efficiency and Connectivity; Center for Connected Multimodal Mobility: Clemson, SC, USA, 2019; p. 86.
- Seo, J.; Duque, L.; Wacker, J. Drone-Enabled Bridge Inspection Methodology and Application. Autom. Constr. 2018, 94, 112–126.
- 22. Sankarasrinivasan, S.; Balasubramanian, E.; Karthik, K.; Chandrasekar, U.; Gupta, R. Health Monitoring of Civil Structures with Integrated UAV and Image Processing System. Procedia Comput. Sci. 2015, 54, 508–515.
- 23. Ayele, Y.Z.; Aliyari, M.; Griffiths, D.; Droguett, E.L. Automatic Crack Segmentation for UAV-Assisted Bridge Inspection. Energies 2020, 13, 6250.
- Chen, J.; Wu, J.; Chen, G.; Dong, W.; Sheng, X. Design and Development of a Multi-Rotor Unmanned Aerial Vehicle System for Bridge Inspection. In Intelligent Robotics and Applications; Kubota, N., Kiguchi, K., Liu, H., Obo, T., Eds.; Lecture Notes in Computer Science; Springer International Publishing: Cham, Switzerland, 2016; Volume 9834, pp. 498–510. ISBN 978-3-319-43505-3.
- 25. Roca, D.; Lagüela, S.; Díaz-Vilariño, L.; Armesto, J.; Arias, P. Low-Cost Aerial Unit for Outdoor Inspection of Building Façades. Autom. Constr. 2013, 36, 128–135.
- HekmatiAthar, S.; Goudarzi, N.; Karimoddini, A.; Homaifar, A.; Divakaran, D. A Systematic Evaluation and Selection of UAS-Enabled Solutions for Bridge Inspection Practices. In Proceedings of the 2020 IEEE Aerospace Conference, Big Sky, MT, USA, 7 March 2020; pp. 1–11.
- 27. Yu, K.; Shanthakumar, P.; Orevillo, J.; Bianchi, E.; Hebdon, M.; Tokekar, P. View Planning and Navigation Algorithms for Autonomous Bridge Inspection with UAVs. arXiv 2019, arXiv:191002786.
- 28. Bolourian, N.; Hammad, A. LiDAR-Equipped UAV Path Planning Considering Potential Locations of Defects for Bridge Inspection. Autom. Constr. 2020, 117, 103250.
- 29. Jung, S.; Choi, D.; Song, S.; Myung, H. Bridge Inspection Using Unmanned Aerial Vehicle Based on HG-SLAM: Hierarchical Graph-Based SLAM. Remote Sens. 2020, 12, 3022.
- 30. Spencer, B.F.; Hoskere, V.; Narazaki, Y. Advances in Computer Vision-Based Civil Infrastructure Inspection and Monitoring. Engineering 2019, 5, 199–222.
- 31. Bhowmick, S.; Nagarajaiah, S.; Veeraraghavan, A. Vision and Deep Learning-Based Algorithms to Detect and Quantify Cracks on Concrete Surfaces from UAV Videos. Sensors 2020, 20, 6299.
- Chaiyasarn, K.; Khan, W.; Ali, L.; Sharma, M.; Brackenbury, D.; Dejong, M. Crack Detection in Masonry Structures Using Convolutional Neural Networks and Support Vector Machines. In Proceedings of the 35th ISARC, Berlin, Germany, 20–25 July 2018; pp. 118–125.

- Saleem, M.R.; Park, J.-W.; Lee, J.-H.; Jung, H.-J.; Sarwar, M.Z. Instant Bridge Visual Inspection Using an Unmanned Aerial Vehicle by Image Capturing and Geo-Tagging System and Deep Convolutional Neural Network. Struct. Health Monit. 2021, 20, 1760–1777.
- 34. Morgenthal, G.; Hallermann, N.; Kersten, J.; Taraben, J.; Debus, P.; Helmrich, M.; Rodehorst, V. Framework for Automated UAS-Based Structural Condition Assessment of Bridges. Autom. Constr. 2019, 97, 77–95.
- 35. Omar, T.; Nehdi, M.L. Remote Sensing of Concrete Bridge Decks Using Unmanned Aerial Vehicle Infrared Thermography. Autom. Constr. 2017, 83, 360–371.
- 36. Mac, V.H.; Tran, Q.H.; Huh, J.; Doan, N.S.; Kang, C.; Han, D. Detection of Delamination with Various Width-to-Depth Ratios in Concrete Bridge Deck Using Passive IRT: Limits and Applicability. Materials 2019, 12, 3996.
- Hiasa, S.; Birgul, R.; Necati Catbas, F. A Data Processing Methodology for Infrared Thermography Images of Concrete Bridges. Comput. Struct. 2017, 190, 205–218.
- Washer, G.; Fenwick, R.; Bolleni, N. Effects of Solar Loading on Infrared Imaging of Subsurface Features in Concrete. J. Bridge Eng. 2010, 15, 384–390.
- 39. Ellenberg, A.; Kontsos, A.; Moon, F.; Bartoli, I. Bridge Deck Delamination Identification from Unmanned Aerial Vehicle Infrared Imagery. Autom. Constr. 2016, 72, 155–165.
- 40. Shen, Z.; Cheng, C.; Na, R.; Shang, Z. To Automate Detecting, Quantifying and Mapping of Delamination via Arial Thermography; Nebraska Department of Transportation: Lincoln, NE, USA, 2020; p. 44.
- 41. Youn, W.; Ko, H.; Choi, H.; Choi, I.; Baek, J.-H.; Myung, H. Collision-Free Autonomous Navigation of A Small UAV Using Low-Cost Sensors in GPS-Denied Environments. Int. J. Control Autom. Syst. 2021, 19, 953–968.
- 42. Mebarki, R.; Lippiello, V.; Siciliano, B. Nonlinear Visual Control of Unmanned Aerial Vehicles in GPS-Denied Environments. IEEE Trans. Robot. 2015, 31, 1004–1017.
- 43. Chowdhary, G.; Johnson, E.N.; Magree, D.; Wu, A.; Shein, A. GPS-Denied Indoor and Outdoor Monocular Vision Aided Navigation and Control of Unmanned Aircraft. J. Field Robot. 2013, 30, 415–438.
- 44. Dehbi, Y.; Klingbeil, L.; Plümer, L. UAV mission planning for automatic exploration and semantic mapping. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 2020, XLIII-B1-2020, 521–526.
- 45. Whitley, T.; Tomiczek, A.; Tripp, C.; Ortega, A.; Mennu, M.; Bridge, J.; Ifju, P. Design of a Small Unmanned Aircraft System for Bridge Inspections. Sensors 2020, 20, 5358.
- 46. González-deSantos, L.M.; Martínez-Sánchez, J.; González-Jorge, H.; Navarro-Medina, F.; Arias, P. UAV Payload with Collision Mitigation for Contact Inspection. Autom. Constr. 2020, 115, 103200.
- Myeong, W.C.; Jung, K.Y.; Jung, S.W.; Jung, Y.H.; Myung, H. Development of a Drone-Type Wall-Sticking and Climbing Robot. In Proceedings of the 2015 12th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI), Goyang, Korea, 28 October 2015; pp. 386–389.
- 48. Kocer, B.B.; Tjahjowidodo, T.; Pratama, M.; Seet, G.G.L. Inspection-While-Flying: An Autonomous Contact-Based Nondestructive Test Using UAV-Tools. Autom. Constr. 2019, 106, 102895.
- 49. Sreenath, S.; Malik, H.; Husnu, N.; Kalaichelavan, K. Assessment and Use of Unmanned Aerial Vehicle for Civil Structural Health Monitoring. Procedia Comput. Sci. 2020, 170, 656–663.
- 50. Liu, Y.; Nie, X.; Fan, J.; Liu, X. Image-based Crack Assessment of Bridge Piers Using Unmanned Aerial Vehicles and Three-dimensional Scene Reconstruction. Comput.-Aided Civ. Infrastruct. Eng. 2020, 35, 511–529.
- 51. Feroz, S.; Abu Dabous, S. UAV-Based Remote Sensing Applications for Bridge Condition Assessment. Remote Sens. 2021, 13, 1809.
- 52. Gucunski, N.; Imani, A.; Romero, F.; Nazarian, S.; Yuan, D.; Wiggenhauser, H.; Shokouhi, P.; Taffe, A.; Kutrubes, D. Nondestructive Testing to Identify Concrete Bridge Deck Deterioration; Transportation Research Board: Washington, DC, USA, 2013; ISBN 978-0-309-12933-6.
- 53. Cheng, C.; Shang, Z.; Shen, Z. Automatic Delamination Segmentation for Bridge Deck Based on Encoder-Decoder Deep Learning through UAV-Based Thermography. NDT E Int. 2020, 116, 102341.
- 54. Tomita, K.; Chew, M.Y.L. A Review of Infrared Thermography for Delamination Detection on Infrastructures and Buildings. Sensors 2022, 22, 423.
- 55. Rahman, A.; Wu, Z.Y.; Kalfarisi, R. Semantic Deep Learning Integrated with RGB Feature-Based Rule Optimization for Facility Surface Corrosion Detection and Evaluation. J. Comput. Civ. Eng. 2021, 35, 04021018.
- 56. Chen, Q.; Wen, X.; Lu, S.; Sun, D. Corrosion Detection for Large Steel Structure Base on UAV Integrated with Image Processing System. IOP Conf. Ser. Mater. Sci. Eng. 2019, 608, 012020.

- 57. Pfändler, P.; Bodie, K.; Angst, U.; Siegwart, R. Flying Corrosion Inspection Robot for Corrosion Monitoring of Civil Structures—First Results. In Proceedings of the SMAR 2019-Fifth Conference on Smart Monitoring, Assessment and Rehabilitation of Civil Structures-Program, Potsdam, Germany, 27–29 August 2019.
- 58. Pryor, G. Utilizing Unmanned Aerial Vehicles (UAVs) for the Estimation of Beam Corrosion of Steel Bridge Girders. Master's Thesis, University of Massachusetts Amherst, Amherst, MA, USA, 2021.
- 59. Dorafshan, S.; Campbell, L.E.; Maguire, M.; Connor, R.J. Benchmarking Unmanned Aerial Systems-Assisted Inspection of Steel Bridges for Fatigue Cracks. J. Transp. Res. Board 2021, 2675, 154–166.
- 60. Chen, S.; Laefer, D.F.; Mangina, E.; Zolanvari, S.M.I.; Byrne, J. UAV Bridge Inspection through Evaluated 3D Reconstructions. J. Bridge Eng. 2019, 24, 05019001.
- 61. Perry, B.J.; Guo, Y.; Atadero, R.; van de Lindt, J.W. Streamlined Bridge Inspection System Utilizing Unmanned Aerial Vehicles (UAVs) and Machine Learning. Measurement 2020, 164, 108048.

Retrieved from https://encyclopedia.pub/entry/history/show/51180