Bridge Inspection: Human Performance, Unmanned Aerial Systems and Automation

Sattar Dorafshan[a*],
Marc Maguire[b],
Department of Civil & Environmental Engineering, Utah State University, Logan, Utah, USA, 84322-4110
[a] PhD Candidate
[b] PhD, Assistant Professor
[*]Corresponding Author, Department of Civil and Environmental Engineering, 4110 Old Main Hill, Logan, Utah 84321-4110, Tell: 001-435-757-3740, E-mail Address: sattar.dor@aggiemail.usu.edu.

Abstract

Unmanned Aerial Systems (UASs) have become of considerable private and commercial interest for a variety of jobs and entertainment in the past 10 years. This paper is a literature review of the state of practice for the United States bridge inspection programs and outlines how automated and unmanned bridge inspections can be made suitable for present and future needs. At its best, current technology limits UAS use to an assistive tool for the inspector to perform a bridge inspection faster, safer, and without traffic closure. The major challenges for UASs are satisfying restrictive Federal Aviation Administration regulations, control issues in a GPS denied environment, pilot expenses and availability, time and cost allocated to tuning, maintenance, post-processing time, and acceptance of the collected data by bridge owners. Using UASs with self-navigation abilities and improving image-processing algorithms to provide results near real-time could revolutionize the bridge inspection industry by providing accurate, multi-use, autonomous three-dimensional models and damage identification.

Keywords: Unmanned Aerial Vehicles, Unmanned Aerial Systems, Bridge Inspections, Bridge 3D Modeling, Damage Detection, Unmanned Inspections.

1 Introduction to Bridge Inspection

According to the Federal Highway Administration's (FHWA) annual report, the number of deficient bridges in the United States was 142,915 in 2015, which is more than 23% of the of the total number of bridges in the United States [1]. The deficiency ratio, defined as the ratio of structurally and non-structurally deficient bridges, to total number of bridges, has decreased significantly from 38% in 1992 to 23% in 2015. Fig.1 shows the deficiency ratio of the United States' bridges based on the latest annual report from FHWA from 1992 through 2015. This trend suggests gradual, but consistent improvement of bridge inventory conditions over the past 21 years. However, the American Society of Civil Engineers (ASCE) gives a grade of C^+ for the United States infrastructure [2]. Improvements in inspection efficiency may allow bridge maintenance engineers and managers to do more inspections at a lower cost. The FHWA stopped tracking non-structurally deficient bridges effective with the 2016 archived data. The number of structurally deficient bridges in 2016 was 54,365 which was 9% of the total number of bridges.

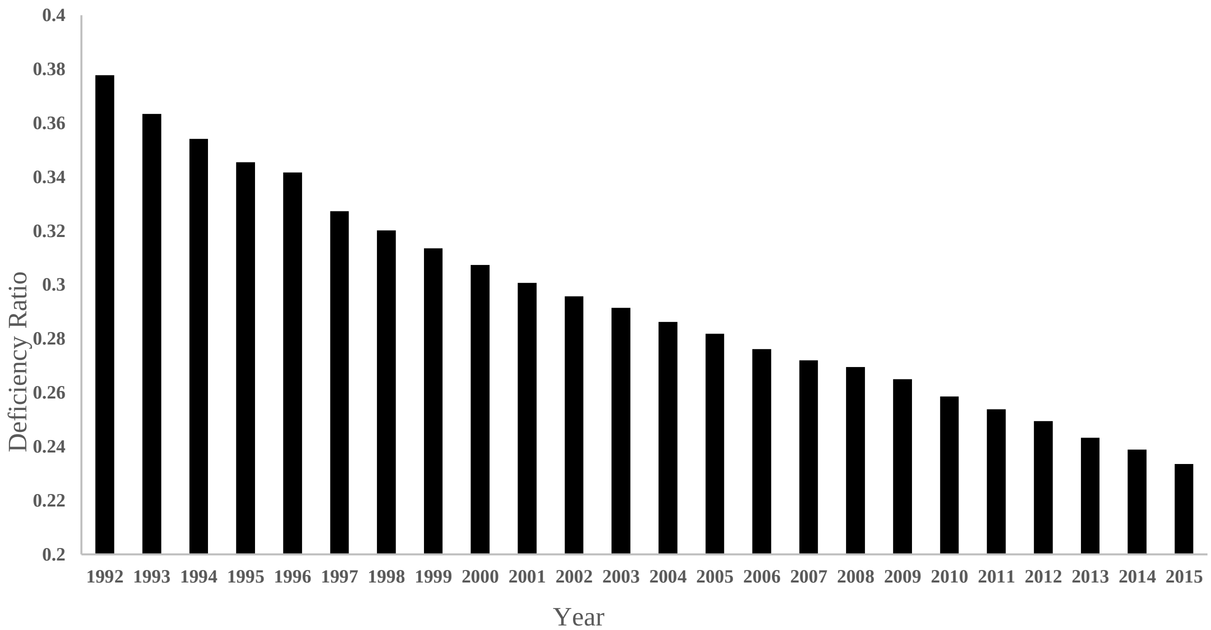

Fig.1 Gradual decrease in deficiency ratio of the bridges in United States since 1992 to the last published data in 2015

Every bridge deteriorates as it ages and is managed by a Bridge Management System (BMS) that often takes into account stochastic processes based on routine bridge inspection information [3,4]. The evolution of bridge inspections in the United States is tied to high profile collapses. Currently, inspections are performed periodically, usually on a 24-month cycle, allowing the inspectors to monitor the defects and deterioration.

1.1 Bridge Inspection Program Evolution

The West Virginia bridge failure, also known as the Silver Bridge collapse, occurred at 5 p.m. on December 15, 1967, when an eyebar-to-pin connection fractured, causing a 445 m portion of the bridge to collapse and resulted in 46 casualties [5]. After this incident, federal authorities decided to coordinate bridge management programs throughout the United States by introducing the Federal Highway Act of 1968. The National Bridge Inspection (NBI) program was initiated to enforce periodic inspections of bridges in 1968 as a direct result of this act. This program was expanded to the National Bridge Inspection Standards (NBIS) in 1971 to prescribe the proper inspection process and frequency and to designate official bridge inspectors [6].

The Mianus River bridge collapse on I-95 in 1983, which was due to hanger assemblies, and the Schoharie Creek bridge failure in 1987, which was due pier scour, heightened concerns over bridge inspection procedures [7]. After these incidents, federal authorities provided guidelines regarding inspection of fracture critical and underwater members. The NBIS was constantly being revised but was the only reference for inspectors in the United States until

1991 when congress mandated that the state Departments of Transportation (state DOTs) come up with a comprehensive state-specific BMS [8]. Part of this program included development of a rigorous software package called “PONTIS” which is a decision-making tool bridge managers use for bridge evaluations and is constantly updated with reports, pictures, core logs, and other relevant bridge data [9,10]. At the same time, the National Cooperative Highway Research Program (NCHRP) developed a BMS software termed “BRIDGIT.” The goal of BRIDGIT was to provide guidelines to manage decisions for either local or state bridge inspection agencies [11].

FHWA has been in charge of preparing and updating a national inspection procedure manual since 1990 called the Bridge Inspector’s Reference Manual (BIRM) [12]. This manual has also been updated several times and includes different methods, technologies, and procedures for inspection. In addition, the National Bridge Inventory (NBI) has gathered more than 14 million inspection data since 1983, which is accessible to the public on the FHWA website [13]. Dekelbab et al. called this database the most comprehensive source of information on bridges in the United States [14]. Fig.2 summarizes the history of bridge inspection manuals and programs since 1968.

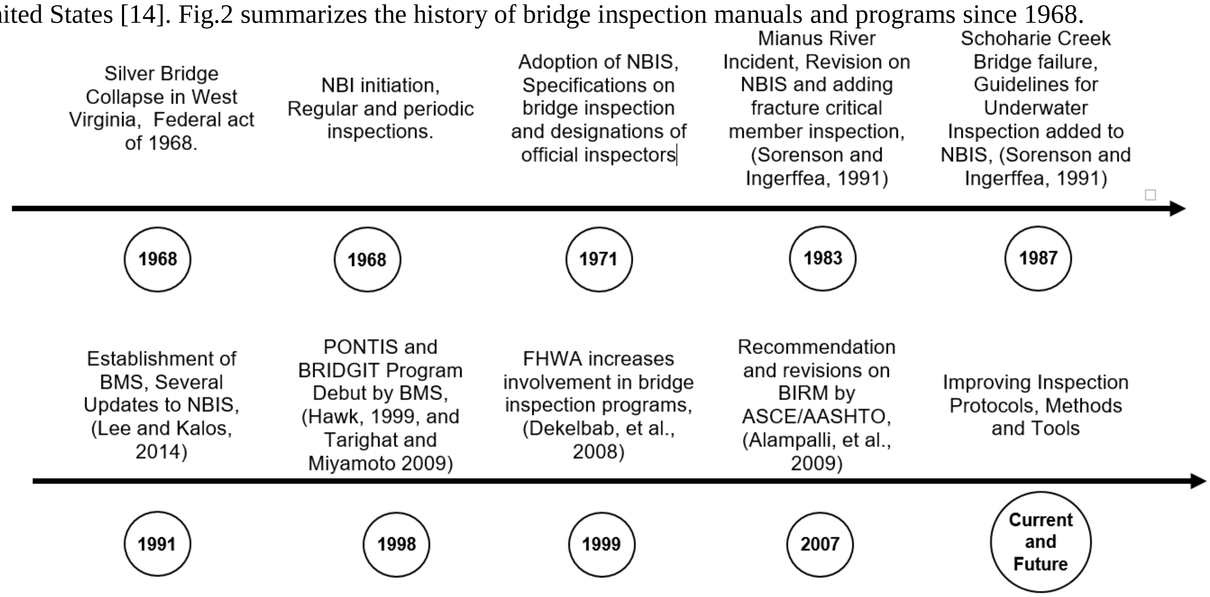

Fig.2 A time-line review on bridge inspection regulations in the United States since 1968 to the last published data in 2018

1.2 Visual and Physical Inspections

Visual inspections are the oldest and most frequent type of bridge inspection. Visual inspections can involve walking on the deck, using binoculars to see a point of interest, or using either scaffolding or an Under Bridge Inspection Truck (UBIT) for regions that are difficult to access. BIRM defines two types of methods for hard-to-reach areas: access equipment and access vehicles. The equipment includes ladders, rigging, scaffolding, boats, climbers, floats, boatswain chairs, free climbing, etc. The most common access vehicles used in bridge inspection practice are man-lifts, scissor lifts, bucket trucks, and UBIT [12]. UBITs provide a proper view of hard to reach areas for inspectors, but they have high capital and maintenance costs. UBITs are difficult to schedule since only a small number of them are in service in any given region. Other issues with UBIT inspections are potentially endangering the public and inspectors, adding additional weight to the bridge, congesting traffic lanes, and most important, UBIT inspections require skilled and qualified workers to operate them [15]. These indirect costs often result in considerably more burden to inspection agencies than the direct costs, making UBIT-free inspections very attractive to many DOTs.

Physical inspections are recommended when visual inspections are not sufficient for rating a certain region, in other words, uncertainty of defect presence or measurement requirements of a member or a defect. The most common practice for physical inspections of bridge slabs uses a sounding hammer and chain drag to locate delaminated regions by comparing the resonating sounds of the defected and undamaged areas [12]. Physical inspection of steel members includes finding under-paint defects to detect fatigue cracks, rust, and corrosion using wire brushes, grinding, and sand blasting. More comprehensive information on physical inspections can be found in the BIRM.

1.3 Advanced Inspections (NDE)

Practitioners and researchers recognized the shortcomings of visual and physical inspections in the 1990's. Rens et al. suggested the following demands for more accurate bridge assessments [16]:

- In-situ structural characteristic determinations
- Accurate evaluation of the current serviceability level
- Economic efficiency
- Degree of dependency on inspector skill or experience

To address these recommendations, Non-Destructive Evaluation (NDE) methods may be applied for bridge inspections. Based on the construction material, there are several NDE inspection methods suggested by BIRM for concrete bridges: Ultrasonic Testing (UT), Ground Penetration Radar (GPR), Impact Echo (IE), Infrared Thermography, Radiography Testing (RT), and Half-cell method; and for steel bridges: Acoustic Emission (AE), Dye Penetrant Testing (PT), Magnetic Testing (MT), Computed Tomography (CT), Eddy Current Testing (ET), and UT. The NDE methods provide essential information for bridge engineers and inspectors; however, these methods have not been practiced widely.

Rolander et al. conducted a survey to determine the state of the practice for high bridge inspection in the United States [17]. One of the questions on this survey was the type and frequency of NDE methods practiced by each DOT at the time of the survey. Forty-one DOTs responded to this question. Chain drag, pachometers, rebound hammers, the half-cell method, GPR, and IE were used for concrete bridges by more than 10 DOTs. NDE methods were utilized more for steel bridges, most likely because most of them are related to fatigue inspections, which are difficult without some form of NDE. Thirty-four, thirty-four, and twenty-seven DOTs used PT, UT, and MT, respectively. This study concluded that DOTs used NDE methods more often than before (California DOT unpublished survey in 1993 was the base), but there was no information about the frequency of using these methods in bridge inspection. A more recent survey by Lee et al. indicated that out of thirty states with their own bridge inspection manuals only eight of them addressed using NDE methods in 2014 [8]. The most practiced NDE method for concrete bridge inspection was GPR, which was used at least once by 77.5% of surveyed state DOTs, while half of the surveyed states used AE during their inspections. All surveyed states used PT at least once for steel bridges. MT and UT were the second most frequently used NDE methods in steel bridges with a 95% exposure rate. The remaining NDE methods for steel bridges either were not used or were reported to be "very difficult" to use, suggesting that major changes in current NDE methods are necessary to minimize human involvement [18].

State DOTs considered visual inspection as the most frequent inspection method in the surveys [8,17]. As it will be explained later in the paper, UASs, an assistive tool for inspectors to perform visual inspections, can save time and money in DOTs. However, with the exception of visual sensors, the non-contact NDE techniques available for UASs, like various spectra cameras, may require time and effort for state DOT acceptance.

There is always a need for cost reductions and improvement to bridge inspection procedures as funding is always a constraint for bridge managers. This section has identified several techniques that can arguably provide more detailed data than traditional visual and physical inspections but may not be worth the time, effort, post-processing, and associated cost. This section also illustrated inspectors' reluctance to adopt new techniques. There is a need to reduce the inspection time and increase inspector and public safety all while decreasing inspection costs, which indicates a need for automated inspection. If unmanned inspection processes are going to replace current standard practices, then they must be robust and require similar time and effort to current practices. The following sections will investigate recent efforts to do so.

1.4 Unmanned/Automated Inspections

Visual and physical inspections are still considered the most reliable and common bridge inspection methods. In other industries (e.g., aerospace and automotive), the role of human errors in inspection have been scrutinized, evaluated, and limited for decades. Automated inspection devices equipped with software packages are now the routine inspection protocol in aviation industry [19]. Unmanned/Automated inspection and maintenance approaches in high-tech industries are the best choice to achieve minimum failure and optimum maintenance level [20]. However, as discussed in the previous section, few inspection agencies are interested in routine NDE use outside of a handful of fatigue crack detection techniques, which essentially augment the inspector's ability to visually identify cracks.

Unmanned/automated methods have the potential to improve and automate the bridge inspection practice. On a small scale, these methods have been performed using either ground or airborne vehicles in the past. The first of robotic vehicles for bridge inspection were ground vehicles and were used for deck inspections. For example, the RABIT Bridge Deck Assessment Tool [21], is a multi-sensor robot used to detect surface and subsurface defects in a bridge deck. The onboard sensors mounted on RABIT were: impact echo, ultrasonic surface wave testing, GPR, electrical resistivity, and a high-resolution digital camera. The RABIT was able to collect data of bridge decks at a rate of 372 square meter per hour, longer than a typical visual inspection, but acquiring considerably more data [22]. RABIT was able to successfully characterize and detect the most common deterioration types in concrete decks including rebar corrosion, delamination, and concrete degradation [23].

Another example is a climbing robot to monitor reinforced concrete structures (under bridge). This robot is capable of detecting corrosion at early stages using electron bombardment [24]. The robot's movement is facilitated through movable suction cups, allowing inspection in hard-to-reach regions.

Lim et al. claimed that visual bridge deck inspections can be performed more accurately if they are performed autonomously [25]. A Robotic Crack Inspection and Mapping (ROCIM) robot was designed to replace human inspections and was capable of autonomous crack detection using a visual mounted camera and integrated edge detector software. In addition, a genetic-based path-planning algorithm was developed to locate turns and determine the traveling distance.

La et al. equipped the RABIT with an autonomous system for deck inspection using impact-echo, ultrasonic, and electrical resistivity [26]. The system was able to navigate autonomously on a bridge deck, detecting cracks and delamination and evaluating the concrete modulus.

The above examples are the first generation of automated or semi-automated inspections with ground vehicles. Within the last decade, UASs have evolved and have obtained unprecedented capabilities and near ubiquity. Many sectors are taking advantage of these new capabilities to transform their industries. The capabilities of UASs and how they relate to bridge inspection are outlined in the following section. A recent review of the robotic infrastructure inspection can be found in [27]

2 UASs and Their Applications

Before moving on to current research on UAS based bridge inspections, a review of UAS definitions and applications is necessary. This review also includes a summary of UAS control and sensors.

2.1 UAS Definition

According to the Unmanned Aerial Vehicle System Association (UAVSA), a UAS is a combination of an Unmanned Aerial Vehicle (UAV), either fixed-wing aircraft, a multi-copter aircraft, the payload (what it is carrying), and the ground control system which is controlled by a human to some degree. UASs are generally defined as any aircraft or aerial device which is able to fly without an onboard human pilot. They are also known as remotely piloted aircrafts, remotely operated aircrafts, remotely piloted vehicles, drones, and remote controlled helicopters. Depending on the purpose for which the UAS is being used, their properties vary, including the number and weight of the mounted sensors, maximum flight altitude, maximum flight duration, etc. UAVs can be fixed wing or vertical take-off and landing (VTOL) platforms.

2.2 Brief UAV History

The very first appearance of UASs in the United States goes back a century ago. Shortly after the first successful development of man-operated aircrafts as the United States entered World War I (WWI), automated unmanned aircrafts were designed to bomb enemy targets. However, this operation was canceled because of engine failure and consecutive setbacks. Also during WWI, the Germans developed an unmanned aircraft that performed one-way missions at a maximum speed of 650 km/h and an altitude of 300 m. At the beginning of the modern era, from 1959 to the present, the main use of UASs was exclusively military. UASs have played an important role in United States' victories and air superiority in different missions and threats [28]. The dominant market for UASs has been and still is military applications.

Within the last 20 years, UASs have found their way into civilian applications. Fig.3 shows an overview of UAS civilian applications and predicts the financial investments in this market until 2017 for each category in Europe [29]. Government applications were predicted to become the major market from 2014 onwards. The fire fighting and agriculture applications will be the second dominant market followed by the energy sector and earth observation until 2017. In addition, the government applications of UASs have been the most progressive market during the past five years of this study. Infrastructure maintenance programs (e.g. bridge inspections) are considered a sub-category of the government market and are just now beginning to be explored as an option for inspections.

UAS applications for civilian purposes have expanded significantly over the past decade and seem to be rising dramatically due to their low cost and tangible scientific improvements. Table 1 demonstrates the recent UAS applications in various fields. For each application, references have been provided for further reading.

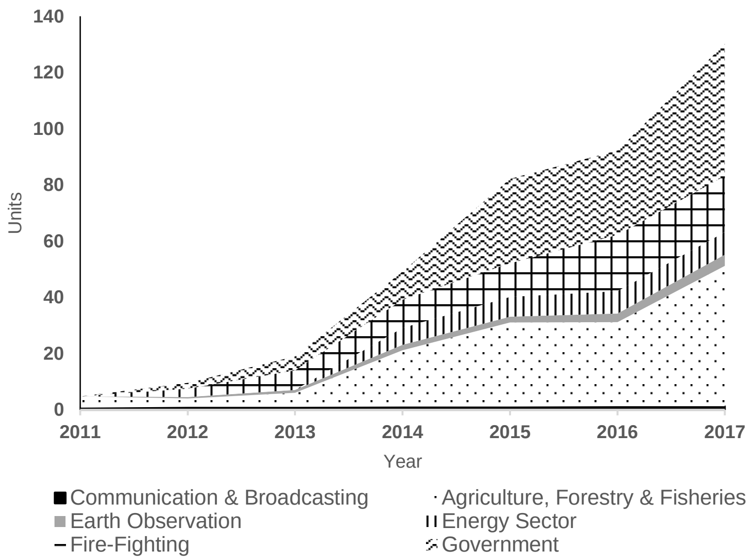

Fig.3 The rising market of UASs for civilian application (Adapted from [29])

Table 1. Variety of UASs applications

Application		Purpose	Reference
Military		Warfare	[28]
		Reconnaissance	[131]
		Intelligence	[28]
		Surveillance	[132]
		Anti-Terrorism	[133]
Civilian	Agriculture and Forestry	Crop Condition Monitoring	[134]
		Fertilization of Trails	[135]
		Properties of Plants	[136]
		Crops Treatment	[137]
		Nitrogen Emission	[138]
		Plant Detection	[139]
		Measurement of Tree Locations	[140]
		3D Mapping of Forest	[141]
	Disaster Monitoring and Management	Hurricane, Typhoons, and Tornados	[142]
		Earthquakes-Damage Evaluation With 3D Model	[143]
		Fire Detection	[144]
		Nuclear Leaks	[145]
		Oil Spill Detection	[146]
		Floods and Avalanches	[147]
		Rescue Missions	[148]
	Surveillance	Prevention of Un-Authorized Entry	[149]
	Environmental Monitoring	Soil Erosion	[150]
		Ground Surveys	[151]
	3D Mapping	Terrain Models	[152]
		Topographic Maps	[153]
		Mapping Landfill	[63]
		Building Models	[154,155]
		Shaded Objects Models	[156]
		Structure Models	[157]
		Archeologic Sites	[158]
	Atmospheric	Temperature Monitoring	[159]
	Wildlife Monitoring	Animal Behavior	[160]

2.3 UAS Sensors

The type and number of sensors mounted on a UAS depends on the mission requirements. In most cases, the sensors on a UAS must be non-contact, significantly limiting the possible NDE techniques. The most popular sensors for evaluating the structure are visual and thermal cameras. There is also a suite of sensors available that are necessary to perform autopilot functions. This section introduces the most common sensors mounted on UASs and their applications.

2.3.1 Visual Cameras (Video/Image)

Visual sensors are the most common sensors and are widely used on UASs for remote sensing purposes. The spectral range of these sensors is in the visible range, in other words, from wavelengths of 390 nanometers to 700 nanometers. Adverse temperatures, lighting conditions, high frequency engines and motors, significant vibrations, and sudden rotation of the UAS can affect the data acquisition process.

2.3.2 Thermal Infrared (TIR) Sensors

Thermal sensors are able to measure the emitted energy of a surface and convert that into temperature. There are two approaches used in infrared thermography: passive and active. The passive approach relies on the thermal properties of just the material and structures, which have a different temperature than the ambient temperature of the specimen. In active thermography, an external heat/cooling source is used to excite the material surface, allowing the TIR sensors to find the difference in thermal signature of specimens in different locations. However, in a bridge inspection situation, passive thermography using only the ambient heat generated by the sun is probably the only feasible option. Thermography is an established method for subsurface defect detection in concrete bridge decks and girders and can be used to generate a comprehensive thermal map [30,31].

2.3.3 Other Sensors

There are several other sensors available that a UAS could employ, which are currently limited due to sensors' weights and UASs' capabilities:

- **Light Detection and Ranging (LiDAR) sensors:** Measures distances and explores the scene by projecting light to the object of interest. These sensors can be used to reconstruct 3D models and maps from the object of interest or provide information to the UAS regarding obstacle avoidance [32].
- **Multispectral and Hyperspectral Sensors:** The spectral bands visible to multispectral and hyperspectral sensors are greater than visual or thermal cameras because they cover a wider range of wavelengths [33].
- **Radio Detection and Ranging (RADAR)/Synthetic Aperture RADAR (SAR):** The installation of SAR on UASs was reported in several resources related or unrelated to bridge inspection [34-35]. The main application of RADAR and SAR is for underwater measurements, which could possibly provide information regarding bridge scour [36].
- **Sound Navigation and Ranging (SONAR):** In the past, these sensors have been used for surface mapping while flying UASs [37]. The current application for SONAR sensors is obstacle detection; however, SONAR use might be limited in a confined under-bridge space because of hard surfaces and bouncing sound waves.
- **Magnetic sensors:** These sensors can generate magnetic maps in great detail, identify various ferrous objects in the soil, and with enough power and accuracy could potentially generate defect maps in ferrous materials like steel girders [38].
- **Multi-sensors and Data Fusion:** Data acquired from different sensors can be combined using data fusion techniques. For instance, with the combination of a radiometer, visual camera, chemical sensor, and thermal infrared sensors, it is possible to measure relative humidity and temperature, CO_2, luminosity, and wind speed [39,40].

2.4 UAS Navigation

The purpose of this section is to introduce the basics of UAS navigation and the associated sensors. The section explains the role of vital components of a UAS with related references for a reader in the field of structural engineering. Using UASs for infrastructure inspection and maintenance is a fast growing trend, but is often outside the scope of most civil and infrastructure engineers' training, so the information provided herein is intended to aid in comprehension of UAS navigation and limitations.

Nearly every UAS, through its autopilot computer and external sensors, comes with some sort of autonomous control. Control and navigation are important issues in all UAS applications, and most pilots are heavily reliant on basic stabilization routines and GPS signals to maintain position. A 3D hold allows for safe control of a UAS in harsh environmental conditions as well as stabilization for obtaining adequate images. In the realm of bridge inspection, control and navigation issues have been reported to be exceptionally problematic because of the challenges of bridge environments [41]. Several algorithms and methods have been studied for UAS semi-autonomous control and navigation.

UAS control and navigation is commonly carried out by GPS, Inertial Navigation Sensors (INS), Inertial Measurement Units (IMU), Micro-Electro-Mechanical Systems (MEMs), gyroscopes, accelerometers, and Altitude Sensors (AS) that are onboard the UAS and used by the autopilot system [42]. GPS is a radio navigation system that allows land, sea, and airborne users to determine their location and velocity [43]. INS is a navigation aid device that uses a computer, a set of motion sensors, and a set of rotation sensors that continuously calculate the position, orientation, and velocity (direction and speed of movement) of a moving object through IMU without external references. MEMs are the technology used in microscopic devices, particularly those with moving parts [44].

The most common sensors employed for semi-autonomous UAS control are visual cameras due to their availability, ubiquity, and low-cost [45]. Image processing techniques can be employed to generate algorithms that identify certain points or objects, like key points, in a set of images as reference to either make a navigable map or hold a position. More information regarding cameras and algorithms used for this purpose are discussed in the following sections.

LiDAR, laser rangefinders, and ultrasonic sensors are often used by the autopilot to estimate the distance from the UAS to the ground or to close objects, allow mapping, and vertically or 3D hold the UAS. Other common sensors that can provide some help, but tend to be less accurate are magnetometers (i.e., compass [41]) and barometers, which sense the air pressure to estimate vertical position. Many of these sensors are highly valuable for navigation and control, but also have significant limitations, especially when used without GPS. For instance, barometers are affected by wind speed and can cause the UAS to drift and stereo vison systems can cause the UAS to follow the current and drift with the waves when used over water [46].

2.5 Autonomous Navigation

It may be possible to remove humans from routine inspection techniques in several years with the convergence of UAS platforms, sensors, and control improvements. The potential for automated inspections will improve when a combination of sensors outlined in the previous section are used along with various types of navigation algorithms that often involve data fusion techniques [47,48]. For autonomous bridge or infrastructure inspections using self-navigated UASs, three fundamental problems need to be solved: mapping, localization, and path planning.

Mapping is the process where a UAS makes a map of its surroundings for navigational purposes using its onboard sensors [49]. Localization is the process of estimating a UAS's position based on a self-generated map, and path planning is the process of going from point A to B while avoiding obstacles [50,51]. When flying UASs near or under a bridge, GPS signals (an integral part of UAS control for most pilots) will be lost, likely resulting in loss of control and poor image quality. In such scenarios, a combination of IMU, cameras, and laser range finders can be used to simultaneously build a map of the environment and localize itself, however this has not yet been demonstrated as possible [46].

In recent navigational studies, a low-cost 5 MP monochrome or color visual camera set at 14-30 fps was found to be functional for navigational purposes [52,53]. Lemaire et al. proposed use of a monochrome camera that is able to operate at least at 60 fps and a 90-degree gimbal [54]. For proper controlling and navigation, a velocity of 30 fps was proposed to be sufficient in recent studies [45]. As a general rule, images larger than 0.3 Mega Pixel (MP) in size are not appropriate for image-processing techniques, like mapping and localization, because of excessive computational time for current on-board computer configurations [45].

One solution for localization and mapping in a GPS denied environment is called Simultaneous Localization and Mapping (SLAM). SLAM is a style of autonomous navigation, which allows UASs to be controlled in a GPS-denied environment. During the SLAM process, a UAS makes observations and measurements of the surrounding environment using mounted sensors, then landmark recognition and positioning allows the UAS to create a map of the structure and its surroundings [55]. SLAM has different implementations depending on the integrated sensors on the UAS [56]. Implementation of visual SLAM in absence of the GPS signals has drawn the attention of researchers in recent years; however, most of them rely on data fusion acquired from several sensors, such as monocular vision and barometer, and RGB-D cameras by providing color image and per-pixel depth, and etc. [57,58]. Despite the successful implementation, none of these methodologies have been used to navigate autonomously around complex structures such as bridges.

This section discussed the potential for autonomous flights in GPS-denied environments. Using just visual cameras for autonomous navigation and realtime mapping is still an open problem. No actual bridge inspections have been carried out using autonomous navigation and, as such, are severely limited by weather and pilot skill. With current theoretical and software development, sensor technology, and commercial availability, UASs cannot inspect a bridge without mostly manual control and therefore UAS-assisted bridge inspections require skilled pilots [46].

2.6 3D Model Reconstruction

Useful 3D models of bridges could provide a permanent record of condition and dimensions from one inspection to another and could also be used for navigation and control purposes. Most of the work in this area has been on building inspection; however, it should directly relate to bridge and infrastructure inspection.

A two dimensional (2D) image loses the scene depth during photography, but using the line of sight and camera positions from each image, depth can be restored and a 3D model can be constructed. Comparing features together can determine the correspondence level of each image. Development of robust feature detection algorithms is a fast moving research area in the computer science. There are several popular approaches for 3D image reconstruction, such as Structure-From-Motion (SFM) [59], and multi-view-stereo (MVS) [60]. All of which use some form of feature detection, which must be efficient enough to compare each of the images in a set made of possibly hundreds – or thousands in the case of infrastructure inspection – of images, which is computationally expensive. The features are traced back to a sequence of images to form the skeleton of the 3D model based on the feature movements.

To familiarize the reader with common terms in the computer vision area, some of the feature detectors are introduced along with references for further reading. One of the most popular feature detection algorithms is Scale-Invariant Feature Transform, or SIFT, which detects the maxima of Differences of Gaussian (DoG) [61]. SIFT also describes the detected feature, and for this reason it is more commonly called "feature descriptor." Speed Up Robust Features, or SURF, is another powerful feature detector and descriptor in the field of 3D model reconstruction [62]. Table 2 demonstrates some of the most important feature detectors used in image based 3D model reconstruction.

Table 2. Popular feature detectors and descriptors in 3D model reconstruction from 2D images

Feature Detector type	Name of the Method	Reference
Edge Detection	Canny, Sobel, Deriche, Differential, Prewitt, Cross	[73]
Corner Detection	Harris operator, Shi and Tomasi, Level curve curvature, Hessian, SUSAN, FAST	[161]
Blob Detection	Laplacian of Gaussian (LOG), DOG, Determinant of Hessian (DOH),	[162]
Ridge Detection	Hough Transformation, Structure Tensor	[163]
Feature Description	SIFT,SURF, Histogram of Oriented Gradient (HOG), Gradient Location and Orientation Histogram (GLOH)	[164]

A comprehensive summary of 3D model reconstruction studies that applies to structural inspections is shown in Table 3. This table demonstrates the evolution of 3D image reconstruction in civil infrastructure from 2004 (manual reconstruction) to 2017 (automated reconstruction). Furthermore, this table can be used as a starting point for future researchers to select methodologies and sensors for different applications. Useful visual cameras for 3D model reconstruction depend on the level of detail the model will require, and model accuracy can be improved through the use of LiDAR.

Generation of a detailed model for a bridge could be very tedious because of the complexity of the geometry. However, 3D models of bridges can be used for semi-autonomous inspections conducted by UASs [46]. Ideally, the 3D model can provide a virtual map for the UAS to navigate around the bridge and avoid obstacles.

There are off-the-shelf or open-source programs available, either free or commercial, that can reconstruct 3D models. Microsoft Photosynth and Automatic Reconstruction Conduit (ARC3D) are free web services that can reconstruct 3D models from color images. Agisoft Photoscan is a popular commercial software product used to generate 3D models and has been used with some success by the authors [46]. However, generating a model of a 3 m long bridge mock-up autonomously using this software took nearly 8 hours, and the model's accuracy was unsuitable for navigation and inspection. Improvements could be made to that model, but not without considerable additional effort which state DOTs may not desire. As discussed in the NDE section, these advanced techniques need to be easy-to-implement if state DOTs are to use them routinely. Neitzel and Klonowski generated 3D models based on 2D images acquired by UAS using several of these programs and compared the results of these and other programs and also found mixed results [63]. It seems that more developments need to be made in this area for 3D models to be a truly feasible infrastructure inspection option.

Table 3. 3D model reconstruction studies using UAS imagery for buildings

Ref.	Year	Reconstructed Object	Sensor's Type	Approach or Detector	Achievements	Shortcomings
[154]	2004	Buildings	Nikon D 100 Camera	Oblique Photogrammetry Camera Calibration	3D Model Reconstruction of Regular Buildings from single UAS image	Insufficent inspection detail, minimal potential for complex geometry
[165]	2009	Buildings	Integrated LiDAR Line Scan	Laser Scanner To Obtain The Depths	Regenerating 3D Model from LiDAR	Insufficent inspection detail, no details provided on computational time or accuracy
[97]	2009	Bridges	Visual	Manual Stitching	Generating Models for Under Bridge Elements	no details provided on computational time or accuracy
[156]	2010	Buildings, mapping	Video Camera	MVS Clustering	MVS Reconstruction at City Level of Several Buildings	Seven hour Run-time, insufficient inspection detail
[155]	2011	Mapping	Amateur or SLR Camera	Patch-Based MVS Software PCMS	3D surface mapping, possible use for birdge decks	Not applicable for under bridge inspection. No details provided on computational time or accuracy
[166]	2011	Buildings	High Resolution Panasoic Lumix GF1 camera LiDAR	SFM SIFT	3D Model of Buildings, Equal Level of Accuracy as LiDAR Model, accuracy was evaluated (1-3 cm)	No details provided on computational time. The accuracy of the model was not desirable for fine defect detection.
[167]	2012	Mapping	Digital SLR Camera- Canon 550D	MVS Georeferencing	3D Scene Modeling. Compared the Result of MSV to Terrestrial Data.	No details provided on computational time, not suitable for defect detection,
[168]	2012	Pavement	Canon EOS Digital Rebel Xti Camera	MVS SIFT	Pavement Damage Detection From 3D Model, 0.5 cm accuracy	No details provided on computational time, the accuracy computed based not on the defects but on targets
[63]	2012	Mapping	MK Hisight II Camera, Canon Digital Ixus 100 IS Camera	Off-The-Shelf Programs SIFT, PVMS, CMVS	A Comparison Between Available Software Packs for 3D Reconstruction	Position accuracy was not suitable for many defects (10-20 cm), No details provided on computational time
[169]	2013	Buildings	Canon SX230 Camera	Manual Stitching	UAS Review on Structural Health Monitoring and 2D Stitching	Manual model construciton
[65]	2014	Concrete Decks	DSLR Digital Camera	SFM	85% accuracy of crack detection, 3D model construction of the deck, max 0.3 cm difference in the 3D model (deck dimensions), 3 mm difference in detected cracks' width	No field experiment, 10 hours of computational time to create the model, manual model development, noted sensitivity to lighting.
[64]	2014	Post-disater montoritng	Visual Camera	SFM	3D model of Concrete specimens, small and full-scale, report the cracking area, 1 hour to create the model, 6 cm difference in specimen dimensions	Controleld lab experiment, manual model generation, no detection on cracks finer than 0.5 cm, no detection on vertical cracks (with respect to the camera), 0.15 cm difference in crack width
[66]	2014	Mapping, Complex Structures (Electrical Transformers)	12.3MP Olympus E-P1, Laser	SIFT ASIFT MVS Georreferencing	PW software development. Comparison between SIFT and ASIFT, 2 cm maximum difference,	Five hour processing time, not suitable for defect detection.

Detailed 3D model of a bridge for purpose of damage identification has not been constructed successfully yet. The proposed method by Torok et al. and Zheng have the potential to be used for defect detection in bridges but neither of them had been examined in the field [64,65]. Weather, sunlight, temperature, wind and other environmental incidents would change the accuracy of the obtained model. In addition, the images used in those studies were not from UASs. The models constructed from UAS images, in other studies in Table 3, were not detailed enough for defect detection. The other issue with 3D model construction is the required time to create it. Five to 10 hours of model construction time can be very long for bridge inspectors, especially when the goal of the UAS inspection is replace visual inspection. Torok et al., stated the model was created in 1 hour [64]. However, the inspected object was small: 140 cm long column with a cross section of 53 cm by 23 cm. A single pier in a small bridge would be considerably larger and more complex, model reconstruction would likely take much longer. LiDAR seems to be the best option to construct 3D models quickly, although the studies do not mention the cost of using UAS equipped with a LiDAR sensor, which are typically heavy, requiring a larger UAS. In addition, for the output data from LiDAR to become a 3D model, skilled operators are required, which will add to the cost. Recent studies provided their models' accuracy to the ground truth which ranged from 0.5 cm to 10 cm. For these models to be effective in defect detection, an accuracy of a tenth of millimeter is required, which was not provided by any of the investigated studies [46]. Therefore, at this time, the application of UASs for 3D model reconstruction of bridges is limited for navigation purposes rather than defect detection. For the modeling to be of use to navigation, processing times need to be decreased considerably, to near real time. In addition, either free or commercially available 3D software can only construct objects with simple geometries and does so without proper details and are time consuming. Recently developed methods can have better performances than the off-the-shelf software in construction of complex objects, such as Rodriguez-Gonzalvez et al. [66].

2.7 Automated Damage Detection

In order for automated inspections to become a reality, automated damage detection must also work with real time navigation and be able to obtain a condition assessment in a reasonable amount of time. Currently, the most promising bridge and infrastructure inspection method is visual image-based damage detection, which can be used with modified thermal or multi-spectral images. The requirements for these sensors are specific to their application, but sensor resolution needs to be fine enough to capture enough pixels of the defect and sound regions, and in the case of visual crack detection, the pixel intensity gradient must be large enough to distinguish the cracking from sound regions [67]. Thermal imaging has similar requirements, but camera sensitivity is paramount, especially since thermal UAS inspection is limited to passive thermography. Dorafshan et al., was able to detect fatigue cracks in the laboratory with a thermal camera, but only with a 0.2ºC sensitivity camera and a 1ºC sensitivity camera indicated nothing [46].

Image processing techniques are used to detect cracks, which are basically semi-linear objects, such as Canny, Sobel, Fourier transform, and Haar transform edge detectors [68]. Image segmentation techniques, percolation algorithms, and filtering operations are also common for concrete crack detection [69-71]. Sometimes, a combination of several image processing techniques are required for damage identification [72]. Vision based training can further improve defect detection using techniques such as neural networks, wavelet transforms, and fuzzy C-means clustering [73-76]. Mohan and Poobal wrote a critical review on concrete crack detection using image processing methods using visual, thermal, ultrasonic, and laser based images [77]. Autonomous image-based crack detection in steel members (fatigue cracks) is challenging because of their size (0.01-0.1 mm width) [67]. Xu et al. introduced an image-based fatigue crack identification framework using a restricted Boltzmann machine algorithm [78]. The authors proposed an image-based algorithm to find two known fatigue cracks on a steel bridge from UAS images in multiple controlled and uncontrolled conditions [67].

Subsurface defects, like reinforced concrete delaminations, can be identified through thermal imagery [79,80]. Other proven applications of infrared thermography for flaw detection are air blisters and crack propagation in FRP, voids in masonry and concrete members, flaws on painted steel members, rebar corrosion detection, and weld defect detections including lack of fusion, crack, nugget, expulsion, and porosity [81-86]. Two recent successful examples of using UAS-based thermography to find concrete delamination on bridge decks can be find in Omar and Nehdi and Wells and Lovelace [87,88]. Another promising area of use for automated inspections would be post-disaster inspections where damage detection is necessary and many successful inspections have been carried out [89-95].

The above studies indicate the vast opportunities of visual and thermal data for defect detection using common UAS sensors, and many studies have been attempted in the past using UASs or other vehicles. Metni and Hammel developed some of the first real-time concrete crack detection algorithms [96]. In addition, Oh et al., was able to identify reinforced concrete cracks, aided by user input on a bridge in combination with image with an average error of 0.02 mm from a distance of 2.3 m with 96.7% accuracy [97]. Inspired by this robotic system proposed in [97], a semi-autonomous robotic system was proposed to inspect road and train bridges [98].

Recently, a combination of a 3D optical evaluation system and thermal infrared imagery was used to detect spalling and delamination in bridge decks, successfully detecting 4/7 defected areas when comparing to cores, but detected delamination in three sound regions (false positive) [99,100]. For comparison, chain drag reported 5 true positives (5/7) and 3 true negatives (3/3) for the same regions [31]. A canny edge detector combined with a Gaussian smoothing filter as part of pre-processing was programmed into the ROCIM robot (see Section 2.4) and was reported to be successful but not applicable on UASs [101]. Zheng proposed a bridge deck crack detection and measurement technique based on the different normal vector orientation between sound and cracked surfaces, and crack dimensions could be detected within a 10% error from a reconstructed model [65].

Morgenthal and Hallermann assessed the quality of UAS-based structural inspections in different weather conditions on a 44 m tall church structure, a 100 m tall turbine machine house, and a 225 m high chimney [102]. Cracks, rust, spalling, and surface degradation were detectable in the captured images; however, motion of the UAS and wind speed affected the quality of images. Sankarasrinivasan et.al. proposed a top hat transform and HSV threshold operation to identify concrete cracks in UAS images and investigate the feasibility of real-time inspections [103]. Regions with spalls and cracks were said to be successfully detected by this algorithm; however, the number of examined images and number of true positives were not provided or compared to other algorithms. Ellenberg et al., designed an experiment to assess UAS's image ability for structural monitoring and damage quantification using digital image correlation and other imaging, [104], techniques. Using a common 12 MP camera, deflection was estimated within 0.1 mm, and simulated corrosion measurements using a K-means algorithm were measured within 10-13% of error [105]. In addition, a combination of edge detectors, filtering, threshold, and morphological operations were used to detect cracks with 88% true positive and 69% true negative. Dorafshan et al., compared an algorithm based on threshold morphological operations to another image-based crack detection method suitable for UAS real-time detection [72,106]. The comparison showed an improved crack detection accuracy of 41% and 48% and an increase in true negative rates of 46% and 49% for defected and sound datasets. The proposed segmentation method was examined on challenging datasets with irrelevant features in the images such as edges of concrete members, surface clutter, paint stains, and background scenery lines that could be confused with cracks by many image-processing techniques. Implementing Deep Learning Convolutional Neural Networks (DLCNNs) in UAS-assisted inspections showed promising results for concrete deck crack detection without human intervention. The network was trained on a set annotated images (manually labeled as cracked or un-cracked) taken by a point and shoot camera of several bridge decks (98% validation accuracy). The trained network was then used to label new images taken by UAS of other concrete structures autonomously with 88% accuracy [107].

Table 4 shows the summary of the above studies in addition to several new research efforts from 2007 to 2017. Reviewing the literature shows that the largest hurdles are probably a lack of a uniform assessment of accuracy and a baseline dataset for easy comparisons among the different methods.

In this section a review of possible applications of UASs for autonomous damage identification is provided. Past studies showed promising results in terms of finding concrete surface cracks and delamination in an autonomous manner. The performance of the implemented methods in terms of accuracy and time was tied to the cameras used in the inspection and the type of defects. Even though a few studies offered realtime defect detection, but the required framework and software, for bridge inspectors to actually use them, were not discussed. Another gap in the past studies was the lack of comparing visual inspections performed by the inspectors to the ones performed using UASs and damage detection algorithms. However, there are studies comparing UAS to manned inspection (refer to section 5.1), but the performance of the two methods was not compared to each other. The accuracy, cost, and time associated with autonomous defect detection may not be well-analyzed in the reviewed studies. Using these methods requires an extra personnel, familiar with how the algorithms were programmed, which will add costs to the inspections. Human inspection can be superior to autonomous defect detection in their current state since a trained inspector can detect variety of defects. Autonomous defect detection for fatigue cracks using UASs have either failed or had limited success in the past [46]. Performing certain inspections, such as in-depth inspection using some sort of NDE method or under-water inspection, can be either very challenging or impossible using UASs. Despite all the shortcomings, the autonomous defect detection can be helpful during a typical bridge inspection by providing an unbiased approach for conventional concrete defect [67].

Table 4. UASs and damage identification

Ref.	Year	Defect	Sensor Type	Method	Achievements	Shortcomings
[96]	2007	Concrete Deck Crack	10MP camera	Manual detection	Autonomous flight used	No autonomous damage detection. Success only on planar objects perpendicular to camera.
[97]	2009	Concrete Deck Crack	Visual camera, Laser, Gyroscope	Noise removal, edge detection (Seed point method)	Integrated machine vision, and human aid, compares to Canny and Sobel edge detectors	Manual detection, no true positive and true negative reports.
[31]	2013	Concrete Spall	12.3MP DSLR camera,	3D optical bridge evaluation system (3DOBS)	Combining chain drag with infrared thermography, thermal and visual data fusion, destructive testing	3DOBS required close proximity to generate the 3D model, Chain drag more consistent and still requires lane closure. 3D model required surface preparation.
		Concrete Delamination	FLIR SC640 thermal camera	Passive thermography, pattern recognition		
[65]	2014	Bridge Deck Cracking, 3D model of crack	DSLR Camera	Oriented thresholding operation	Crack detection and measurement on 3D model	Thresholding value was user-defined, no field experiments
[101]	2014	Bridge Deck	High resolution visual	LoG	Autonomous crack detection and mapping, realtime crack detection.	No under-bridge inspections, no true/false positive reports.
[102]	2014	Concrete Wall Cracks/Spalls, Steel Rust	Panasonic Lumix DMC TZ 22, 14.1MP and Sony NEX 5 14.2MP	Manual	Discussion of wind effect on UAS performance	Motion blur weakened the visual damage detection, no autonomous defect detection, no comparison to human inspection
		Concrete Wall Crack	Sony NEX 5 14.2MP	Automated computer-vision	probability of detection with clear and blurry images	Less successful crack detection in blurry images due to adverse weather
[103]	2015	Concrete Member Crack, Efflorescence, Surface Erosion	PAL 762*572 camera	Hat transformation, HSV and grey-scale thresholding	Detection of Concrete cracks and degradation	Accuracy not reported, user-defined parameters required, no comparison to human inspection.
[104]	2016	Concrete Member Crack, Beam Deformation, Steel Corrosion	10MP GoPro Hero 3	Median filtering, morphological operation, shape filtering, K-means segmentation.	Deflection measurement, crack detection, corrosion detection	Lab test, stationary camera, no comparison to human performance, accuracy not reported
[72]	2016	Concrete Pavement Crack	12MP Nikon camera	Median filtering, Sobel, HSV thresholding, morphological operations	Crack detection with 90% accuracy in less than 1 s per image, image segmentation using shape, UAS inspection	31% of false positive reports, user-defined values in the algorithm, no comparison to human inspection
[87]	2017	Concrete Delamination	FLIR Vue Pro Thermal Camera	Histogram Equalization, Image Segmentation (K-mean clustering)	Delamination detection comparable to hammer sounding and half-cell potential, two full-scale inspections	No discussion on the effect of temperature, UAS's small payload, sensitive to weather
[46]	2017	Bridge Deck Cracks, Steel Fatigue Cracks	12MP Nikon, 12MP DJI Mavic, 12Mp GoPro Hero 4	Manual Detection, LoG Edge Detector	90% accuracy, Successful fatigue crack detection visually in UAS images, human comparison. Lab and outdoor detection.	Only two (movable) fatigue cracks in the dataset, cracks' size and location were know before inspection
[130]	2017	Bridge Deck Cracks	12MP Nikon	Sobel, Roberts, Gaussian Filter	Comparison between three edge detectors, Wide variety of images.	Images in the datasets had no irrelevant objects, shadows, etc., No filed test or UAS information.
[67]	2017	Bridge Deck Cracks, Steel Fatigue Cracks	12Mp Nikon, 12MP DJI Mavic	LoG and Statistical Thresholding	92% accuracy, less than 1 second per image run time.	Images in concrete dataset were without irrelevant objects, The fatigue crack algorithm only tested on 2 images.
[76]	2017	Concrete cracks	4k Camera	Fuzzy C-means clustering	Detection fine cracks (0.3 mm width) from UAS Images, 90% true crack detection	No information about the camera, highly sensitive to image noise, 80% true negative reports, no comparison to human inspection.
[78]	2017	Steel fatigue cracks	4K Nikon D7000	Restricted Boltzmann machine	Detection of fatigue cracks with 90% accuracy	No UAS inspection,no field tests, user-defined parameters in the algorithm
[77]	2017	Concrete cracks	Visual, thermal, ultrasonic, laser.	Review	Comprehensive review on different methodologies and sensors for concrete crack detection	No discussion on the dataset, no output images for verification.
[107]	2018	Concrte cracks	12Mp Nikon, GoPro Hero 4, 12MP DJI Mavic	Deep Learning Convolutional Neural Networks (DLCNNs)	Successful implementation of DLCNNs trained on high quality images to detect concrete cracks in UAS images autonomously	Limited testing dataset, relative poor performance of the network on UAS images

3 UASs and Bridge Inspections

This chapter is dedicated to published studies and research about using UASs for DOT missions and is organized into two categories: bridge inspection and other applications. UAS applications in bridge inspection have become widespread with state DOTs. According to a survey performed by the American Association of State Highways and Transportation Officials (AASHTO) in 2016, seventeen state DOTs had researched and/or used UASs for certain transportation purposes [108].

The survey also indicated a growing number of state DOTs, either independently or with the aid of one or more academic institutions, are studying UASs and developing policies. Based on a literature search, there are more states involved in UAS research for various purposes since the writing of Dorsey, including but not limited to North Carolina and Utah. Fig.4 shows the states with current or past involvement with UASs for different DOT missions [46].

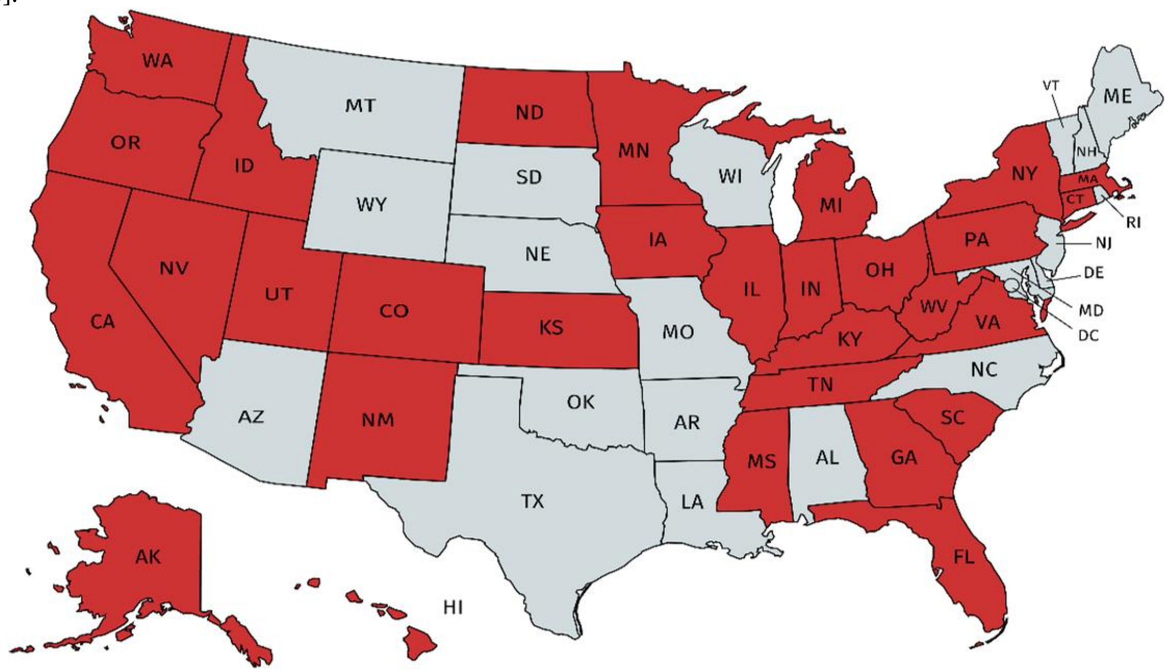

Fig.4 US Map with 34 red shaded states indicating current or past involvement with UAS research and applications (Adapted [46])

3.1 UASs and State DOTs

UASs have been used by departments of transportation for almost two decades [46]. However, state DOTs have used UASs for different reasons. Currently, no DOTs are using UASs for routine bridge inspections, but many are performing investigations in this area. Many states are not investigating UAS assisted bridge inspections at all but are performing some sort of feasibility investigations for evaluation of other infrastructure like traffic, stockpile, and construction monitoring.

3.1.1 DOTs and UAS Bridge Inspections

California DOT

In 2008, California DOT and University of California at Davis published a report on aerial robot bridge inspection [41]. A custom UAS was designed to be tethered to the ground, and therefore was easier to control and conform to Federal Aviation Administration (FAA) regulations at the time. The onboard flight control computer was developed to provide a redundant high-speed communications link to manage the platform stability. However, the project was terminated because it did not result in a fully-deployable aerial vehicle due to the following problems: unreliable heading (compass), instability, especially in wind, and unsuccessful implementation of the altitude hold sensor. The California research project was one of the first research reports published by a DOT on utilizing UASs for bridge inspections.

Georgia DOT

As part of a joint research project with Georgia Institute of Technology in 2014, Georgia DOT published the results of twenty-four interviews with GDOT personnel in order to evaluate the economic and operational advantages and drawbacks of UASs within traffic management, transportation, and construction [109]. Five different UASs configurations, A through E, were investigated in the GDOT study. System A was a quad-motor UAS having FPV, VTOL, and a video camera suitable for monitoring operations such as and not limited to traffic monitoring. System B was an enhanced version of System A, equipped with LiDAR. This system was recommended for any mission that involved mapping. System C also expanded upon System A with emphasis on prolonged environment/region monitoring, for example, construction sites. System D was proposed as a platform for county-sized missions, whereas Systems A through C were for regional missions. System D was a fixed winged aircraft with wingspan size of 2-6 m and capable of high-quality aerial photogrammetry. This system was suggested as the proper candidate for post-disaster response missions and traffic monitoring. Finally, System E configuration, which was recommended for bridge inspections, consisted of a multi-rotor copter with 8 or more motors, potentially tethered, capable of VTOL, and equipped with LiDAR and safety pilot mode.

Michigan DOT

Michigan DOT published the results of experiments on five main UAS platforms with different sensors [100]. These UASs were equipped with a combination of visual, thermal, and LiDAR sensors to assess critical infrastructures and their defects, for example, bridges, confined spaces, traffic flow, and roadway assets. They concluded that UASs are low-cost, flexible, and time-efficient tools that can be used for multiple purposes: traffic control, infrastructure inspections, and 3D modeling of bridges and terrain. Each platform was reported to be suitable for a certain task in Michigan DOT. A VTOL, equipped with a thermal and a visual camera, proved to be the most appropriate for high-resolution imaging of a bridge decks, but obtained mixed results when compared to hammer sounding due to the poor surface quality of the deck. With regard to UAS controls for bridge assessment, SLAM was proposed as a topic for future study with the major challenge being UAS position accuracy.

Minnesota DOT (Phase 1)

Minnesota DOT initiated investigations into benefits and potentials of UAS bridge inspection [15]. In this study, four bridges in Minnesota were inspected using UASs to study the effectiveness of VTOL UASs. The first bridge inspection was a 26 m long single span prestressted concrete bridge, and the UAS could not perform an under bridge inspection due to low-clearance and lack of GPS signals. The human inspection and the UAS inspection detected defects on a bridge deck such as spalls and cracking, but the inspector detected missing anchor bolt nuts during the under-bridge inspection while the UAS was unable to detect this defect. However, mild scour was only detectable in the UAS images. The second bridge inspection was done on a 100 m long open spandrel concrete arch bridge. The UAS was unable to survey the top of the bridge deck due to traffic. Zoom lens provided reasonable visibility for some under-bridge items. In this case, mild scour was not detectable in the UAS images, but the UAS inspection images showed bearing deterioration that the human inspection report missed. On the third structure, a five span steel underdeck truss, the UAS could investigate the truss superstructure and substructure and excellent agreement was found between the human and UAS inspection. The final bridge was approximately 850 m long with five truss arch spans, and a UAS inspection was carried out on this bridge but was not compared to a human inspection. It was concluded that UASs can be used in the field of bridge inspection while posing minimum risk to the public and inspection personnel. In some cases, UAS images provided a cost-effective way to obtain detailed information that may not normally be obtained during routine inspections. FAA regulations prevented the UAS from flying over traffic, negating the benefits of UAS inspections for the deck.

Florida DOT

In 2015, Florida DOT published a research report investigating the feasibility of UAS-assisted inspection of bridges and high mast luminaires [110]. A UAS, equipped with high-definition cameras was used in lieu of experienced inspectors to achieve the following goals: reduce the cost of inspection, reduce the hazards to the inspector, increase the public safety, and increase the inspection effectiveness through more comprehensive data acquisition. Limitations were also identified, such as allowable payloads, control and navigation in severe winds, and image quality in low-light conditions. One aspect of this study was to select the main UAS components based on the demands of the project. Weighted factor analyses were developed to provide a systematic decision-making toolbox for each component, which led to the selection of three VTOL UASs, four ground viewing stations, and three visual cameras. Finally, a dual camera setup, and remote control gimbal were selected to perform the inspections. The selected UAS was tested against wind to determine the required clearance from an object. This clearance was estimated to be 0.3 m for wind speeds less than 11 km/h and wind gusts less than 16 km/h; however, the required clearance is only valid for the tested UAS. UASs were able to inspect a high mast luminaire in 8.5 minutes while providing adequate pictures in acceptable details. Additionally, two preliminary field tests were performed under controlled conditions where a pedestrian bridge and a wooden bridge were inspected under 15 minutes and 10 minutes, respectively. The inspections indicated moderate and severe rust and fine cracks. A field test with FDOT inspectors performed the inspection in 10 minutes under 20 km/h wind speeds and 29 km/h wind gusts, respectively. Rust, cracks through epoxy, bearing deformation, and deck and girder separation were among the detected flaws. The other field test was performed on a steel railroad drawbridge with wind speeds of 11 km/h and the wind gusts equal to 27 km/h. Missing nuts and severely rusted bolts were detected. The third field inspection was performed on a concrete and steel superstructure bridge in 10 minutes while the wind speed was 27 km/h and the wind gusts were 40 km/h This inspection showed mild to severe corrosion regions on a transverse girder bracing and a separation between the girder and the deck in the images. A service and maintenance schedule was proposed for UASs with a 25 hour of operation interval.

Idaho DOT

Idaho Transportation Department (ITD) in corporation with Utah State University conducted a UAS bridge inspection with emphasis on damage detection in bridges with Fracture Critical Members (FCM) [46]. Two aspects of remote sensing in bridge inspections were investigated in this study: visual inspections and autonomous defect detection, both using inspection data gathered by UASs. Several inspections conducted on a lab made bridge using a 3DR Iris platform showing UASs can be used for deck inspections and concrete crack detection in real time. An image processing algorithm was also used to detect cracks automatically with 90% accuracy. The next phase of this study was to determine the feasibility of fatigue crack detection using three UAS platforms: 3DR Iris, DJI Mavic, and a custom-made VTOL. A set of indoor and outdoor experiments in GPS denied environments were carried out. The target of the inspections was to visually detect a real fatigue crack on a test-piece from UAS images in various situations to determine the minimum requirements in terms of clearance and lighting condition. The crack was not visible in the images captured by the 3DR Iris (with a GoPro Hero 4 camera) in any condition. DJI Mavic images were acquired without GPS and in dark lighting conditions (i.e., similar to that under a bridge), showing the fatigue crack. The custom VTOL struggled in GPS denied situations, but the optical zoom on its camera allowed for somewhat successful fatigue crack detection. An image-processing method for autonomous fatigue crack detection was developed which detected more than 80% of the crack length in DJI Mavic images. The DJI Mavic was recommended as a potentially suitable platform for under-bridge inspections due to reliance on a stereo-vision positioning system in absence of the GPS signals, a good quality camera, its small size for maneuvering between girders, and the camera’s ability to function in low light conditions (manual exposure adjustment). This platform however did not perform properly over running water during inspection of an in-service fracture critical bridge in Idaho. Due to the absence of GPS signals under the bridge, the DJI Mavic relied mainly on its downward stereo vision positioning system for control and navigation. Therefore, the UAS did not hold neither did its altitude or its position when it was flown over the current. The performed field study was inconclusive with respect to fatigue crack detection, but was successful in detecting concrete and steel surface deterioration.

Minnesota (Phase 2)

Phase 2 of the Minnesota DOT study was completed in 2017 by inspecting 4 other bridges throughout Minnesota [88]. The inspected bridges were longer than the ones studied in the phase 1 [15]. The UAS performance for bridge inspection was compared to standard hands-on inspection in terms of cost and time, access methods, and data collection. Unlike the phase 1, UAS-based structural condition assessment of the bridges was not compared to the hands-on results. A Sensefly Albris UAS, equipped with a thermal and a visual camera, was used for the inspection. The platform was designed for GPS-denied operation, inspection, and mapping. First, a 2,400 m long multi-span steel bridge constructed in 1961 was inspected. The inspection of this bridge proved that the UASs can successfully be used to navigate around large-scale bridges in severe weather condition. However, the report does not define the severe weather. The UAS provided data from under-bridge members yet, there was no actual indication of defect detection in the report. With $20,000, UAS inspection was claimed to be 66% cheaper than the traditional inspection ($59,000) which included four inspection vehicles, and a 25 m man lift. However, the traditional inspection took 8 days to inspect the bridge while the UAS finished the inspection in 5 days. The second inspected bridge was a 110 m long steel high truss built in 1939. The main objective of this inspection was to detect deck delamination using the integrated thermal camera on the UAS and compare the results to chain dragging and handheld FLIR thermal camera. It was stated that “the onboard thermal sensor was able to detect the deck delaminations with good accuracy”, but this was not quantified. A 3D model of this bridge was also constructed by processing UAS images with Pix4D mapping software, however, no information regarding the quality/accuracy of the model is presented. An 80 m long corrugated steel culvert was the subject of the third inspection. The integrated headlight provided enough illumination to capture usable images; however, UAS thrust kicked up dust, making the images not useful for inspection. The final inspection was done on an 86 years old 10-spanthrough truss bridge, one movable span, and three concrete spans. Reportedly this inspection helped the managers to decide to replace the railing based on the images captured by the UAS.

3.1.2 DOTs and Other UAS Applications

Virginia DOT

Virginia DOT cooperated with the National Consortium on Remote Sensing in Transportation to prove that it is possible to use UASs for traffic surveillance and monitoring [111]. The result of this cooperation showed that the UASs can reduce costs associated with traffic control by 50%.

Ohio DOT

Ohio DOT, in collaboration with Ohio State University in 2005, performed field experiments in Columbus, OH to collect data about freeway intersection movement, network paths, and parking lot monitoring. The outcome of the project provided quasi real-time space planning and distribution from the collected information by UASs to help travelers [112].

Florida DOT

Florida DOT (FDOT) began to investigate the applications of UASs in 2005 with the main focus on traffic management and road monitoring [113].

Washington State DOT

Washington State DOT and the University of Washington investigated the merits and challenges of using UASs to perform traffic surveillance and avalanche control [114]. They conducted experiments on two types of UASs: A fixed-wing aircraft and a VTOL rotary-wing aircraft (helicopter). The fixed-wing UAS was able to collect data from mountain slopes next to highways in case of an avalanche. The VTOL was found to be more suitable for urban area and traffic surveillance.

Utah DOT

Utah DOT in association with Utah State University studied the application of UASs for monitoring and documenting state roadway structures during a highway construction project [115]. Images were also taken to identify the species of wetland plant at Utah Lake wetland mitigation bank. The result of the inspection, after post-processing, was a mosaic model of the scene.

Idaho DOT

ITD initiated a preliminary investigation into UAS in 2014 to look into construction and stockpile monitoring. In this first investigation, visual and thermal images of bridge structures were taken, but were of limited use [46].

3.2 Summary of DOT investigations

Table 5 summarizes goals, achievements, and obstacles in each state DOT research project, organized chronologically by bridge inspection mission or non-bridge related. This table includes all state DOT studies on UASs that have been published or cited by an article in research done between 2002 and 2017. Table 6 presents a summary of the UAS platform and sensor specifications used in state DOTs and is organized chronologically by bridge inspection mission or non-bridge related.

Table 5. UAS's progress and obstacles in state DOTs

Bridge Inspection				
State DOT	**Ref.**	**Goals**	**Achievements**	**Shortcomings**
California	[41]	Routine Bridge Inspection	Vertical takeoff, wind resistance up to 37 kmh, inspection images	Instability
Georgia	[109]	Determining proper UAS configuration for specific tasks	Proposition of five UAS configuration including the type of platform, vehicle, station and number and type of sensors.	No field inspections
Michigan	[100]	Initial Bridge Inspection, delamination detection	Successful construction of point cloud 3D models, defect detection (delamination)	Manual control, inconsistency between thermal and ground true in for delamination detection, inaccurate GPS
Minnesota (Phase 1)	[15]	Initial bridge inspection with off-the-shelf UASs	Structure mapping, thermal inspections, GPS assisted navigation, reasonable agreement between human and UAS inspection	FAA regulations prevented top bridge inspection, Loss of GPS signals prevented under bridge inspections,
Florida	[110]	Initial inspections of bridge and high mast luminaires	Similar image quality compared to human inspector, detection of concrete cracks down to 0.02 inches	FAA regulations prevented top bridge inspection, Loss of GPS signals prevented under bridge inspections, poor control in wind
Idaho	[46]	Fatigue crack detection (FCM inspection), GPS-denied navigation	Autonomous and visual bridge deck condition assessment,	No crack detection in the field inspection, no over water flight due to sonar limitation,

			Autonomous and visual fatigue crack detection in mock inspections, field inspection	
Minnesota (Phase2)	[88]	GPS denied environment, initial inspection of large-scale bridges	Successful delamination detection using thermography, successful GPS-denied navigation, 3D model and mapping, cheaper and faster than traditional inspections for large-scale bridges	No indication to weather effects, no comparison between UAS and human inspection.in terms of defect detection (except for delamination)
Non-Bridge Inspection				
State DOT	**Ref.**	**Goals**	**Achievements**	**Challenges**
Virginia	[111]	Traffic surveillance and road condition monitoring	Cost Saving	N/A
Florida	[113]	Recording data in less time consuming	FAA rule development, proof of concept	Manual control
Ohio	[112]	Freeway traffic assessment	quasi real-time space planning,	Manual control
Washington	[114]	Minimizing the highway avalanche closure and traffic control	Higher flight elevations up to 1500 feet, demonstrating need for flexible FAA regulations	Manual control, restrictive FAA regulations
Utah	[115]	Roadway construction and vegetation monitoring	Successful and high quality images	Manually controlled, inaccurate models of the site, insufficient image overlap

Table 6. UAS Mission Parameters in state DOTs

Bridge Inspection					
State DOT	**Year**	**Model/type**	**Sensors**	**Payload**	**Purpose**
California	2008	ES20-10	Visual Camera	4.5kg	Road Inspection
Michigan	2015	Bergen HexaCopter	Visual and Thermal Camera, LiDAR	5kg	Deck inspection, 3D modeling, roadway assets
		DJI Phantom	Visual camera	unknown	Bridge and construction monitoring
		BlackoutMini Quadcopter	Visual camera	unknown	Bridge structure imaging, confined space assessment
		Heli-Max 1 Si	Visual camera	unknown	Confined space assessment
		Walkera QR 100S	Visual camera	unknown	Confined space assessment
		FVPfactory Waterproof quadcopter	Visual Camera	"Half of vehicle weight"	Bridge structure imaging - undersides (For bridges over water)
		Blimp	Visual Camera	"Half of vehicle weight"	Traffic monitoring and maintenance
Minnesota (Phase 1)	2015	Ayeron Skyranger	Visual and Thermal Camera, Lights	Variable	Bridge inspection
Florida	2015	ArduPilot Mega 2.5 Micro Copter	Visual Camera	Variable	Bridge and high mast pole inspection
Idaho	2017	Custom-made (Goose)	Visual and thermal Camera	14.5kg	Bridge inspection
		DJI Mavic	Visual Camera	0.9kg	Bridge inspection
		3DR Iris	Visual Camera	0.4kg	Bridge inspection and fatigue crack detection
Minnesota (Phase 2)	2017	Sensefly Albris	Visual and Thermal Camera	1.8kg (including the UAS)	GPS-denied navigation, mapping, 3D model construction, bridge inspection.
Non-Bridge Inspection					
State DOT	**Year**	**Model/type**	**Sensors**	**Payload**	**Purpose**
Virginia	2002	ADAS	Visual Camera	-	Proof of concept
Ohio	2004	MLB BAT	Visual Camera	2.2kg	Traffic surveillance and road condition monitoring
Florida	2005	Aerosonde	Visual Camera	13kg	Traffic surveillance
Washington	2008	MLB-BAT R-Max	Visual Camera	2.2kg 29.5kg	Avalanche control, traffic supervision
Utah	2012	AggieAir	Visual Camera	0.9kg	Monitoring, Object detection
Idaho	2014	Sensfly eBee RTk	Visual and Thermal Cameras	0.73kg	Road monitoring

4 FAA Regulations on UASs

4.1 Current Regulations

There are two sets of rules for flying any aircraft: Visual Flight Rules (VFL) and Instrument Flight Rules (IFR). According to the "Aeronautical Information Manual," a controlled airspace is defined as "…an airspace of defined dimensions within which air traffic control service is provided to both IFR and VFR flights in accordance with its classifications" [116]. In the United States, the controlled airspaces are designated as in Table 7.

Table 7. Designated Airspaces in United States (Adapted from [116])

Name of the class	Definitions
Class A	From 5,500m mean sea level (MSL) up to and including Flight Level[1] 600.
Class B	From the surface to 3000m MSL.
Class C	From the surface to 1,200 m (4,000-foot) above the airport elevation.
Class D	From the surface to 760m from the airport elevation.
Class E	An airspace that is not classified as A, B, C, and D
Class G	Uncontrolled airspace with no IFR operation.

1. Flight Level (FL) are described by a nominal altitude in hector-feet while being a multiple of 500-foot. FL 600 is equal to 18,200 m (60,000-foot)

The FAA was established after the Federal Aviation Act in 1958 and was called the "Federal Aviation Agency" at first, until it became a part of the DOT and took on its present name in 1967. One of the responsibilities of this administration was and is to provide safety regulations for flying UASs. FAA recognizes two categories for UAS use: "Fly for fun" and "Fly for work/business." The former does not require permission from FAA, but the vehicle should be registered through the FAA website. The "Fly for work/business" category is restricted by FAA. The latest version of the FAA rules was published on the FAA website on June 21, 2016. Some of these regulations are as follows:

- The total weight of the unmanned aircraft should be less than 25 kg (vehicle and payload).
- The vehicle must remain within the visual line-of-sight of the remote pilot in command, the person manipulating the flight controls, and the visual observer during the flight.
- The aircraft must not operate over any persons that are not directly participating in the operation, are not placed under a covered structure, and are not inside of a covered stationary vehicle.
- Flight is only permitted during day-light or civil twilight with appropriate anti-collision lighting.
- The sole use of a first person view camera does not satisfy the "see-and-avoid" requirements.
- The maximum altitude is 133 m above ground level (AGL) or within 133 m of a structure.
- The maximum speed of the UAS must not exceed 160 km/h.
- No person may act as a remote pilot or visual observer for more than one UAS at the same time.
- The UAS operator must either hold a remote pilot airman certificate or be under the direct supervision of a certificate holder.
- UASs must be registered and certified by the FAA.
- The UAS must not be flown within 8 km of an airport without prior authorization from the airport operators.
- The UAS must not be flown from a moving vehicle.

Pilots requirements are:

- Must be at least 16-years old
- Must pass an initial aeronautical knowledge test at an FAA-approved knowledge testing center
- Must be vetted by the Transportation Safety Administration (TSA)
- Must pass a recurrent aeronautical knowledge test every 24 months.

Registered aircraft must have an application form (AC Form 5050-1) and evidence of UAS ownership. After submitting these documents, the UAS is registered and a Certificate of Authorization (COA) can be requested. The following information is required to submit the COA application form: concept of operation and type of missions, operation location, altitude, communications, and flight procedures [109]. After submission, FAA conducts a comprehensive operational and technical review on the application to ensure the UAS can operate safely with other airspace users. As of 2018, the wait time to complete the application is 60 days. The COA application also requires proof of airworthiness for the UAS. This proof can be obtained either by submitting an Airworthiness Statement or through FAA's Certificate of Airworthiness. As a new interim policy, FAA has been speeding up COA, also known as Certificate of Waiver in section 333 for certain commercial UASs. Section 333 exemption holders now are automatically granted with “blanket 200 foot,” which allows them to fly anywhere in the country except for restricted airspaces, as long as they are below 61 m (200 feet) and the platform is not heavier than 24 kg. The part 107 regulations provide a flexible framework; however, more opportunities have been provided by FAA to omit these regulations. Table 8 demonstrates the summary of the regulations for flying UASs and micro UASs (weight less than or equal to 2 kg).

Table 8. UAS and micro UAS regulations (adapted from [110])

Provision	UAS	Micro UAS
Maximum Weight (platform plus payload)	24 kg	2 kg
Airspace confinements	Class G, and Class B, C, D, E with Air Traffic Center permission	Only Class G
Distance from people and structures	No operation over any person not involved and uncovered	No limitation
Autonomous operations	Yes	No
Required aeronautical knowledge	Knowledge test	Self-certification
FPV	Permitted; if visual line of sight is satisfied	Not permitted
Visual observer training	Not required	Not required
Operator training	Not required	Not required
Operator certificate	Required with knowledge test	Required without knowledge test
Preflight safety assessments	Required	Required
Operation within 8 km of an airport	Prohibited	Prohibited
Operate in congested region	Permitted	Permitted
Liability insurance	Not required	Not required
Night operation	Prohibited	Prohibited

4.2 FAA Restriction to UAS Bridge Inspection

The previous section illustrated the current FAA regulation on using UASs. These regulations pose limitations on the certain aspects of UAS bridge inspection which will be discussed in this section.

- FAA mandates the pilot has a line-of-sight to the vehicle during the inspection. However, one of the advantages of using UASs is to access to locations that are difficult to reach without a UBIT [46,117,118]. Maintaining the line-of-sight becomes impossible for certain terrain and topographical situations, severely limiting inspection. It may be possible to obtain a waiver for these situations.
- Past studies indicate bridge deck inspection is one of the strength of UASs over human inspector in terms of cost and time of inspection [31,88]. However, the current FAA regulations prohibit UASs over passing traffic, requiring lane closure. Waivers for flight over traffic are possible, however, the proximity to said traffic will be a deciding factor.
- One of the proven techniques for deck delamination detection in using thermal inertia which requires taking thermal image of a surface in two different ambient temperatures with maximum possible temperature gradient, i.e., daytime and nighttime [80], yet the FAA limits the UAS operation to daytime.
- According to FAA regulations, the maximum flight altitude is 133 m. Therefore, any bridge elevated more than 133 m cannot be inspected while one of the merits of using UASs is to provide data on bridges that are challenging such as tall bridges. There are almost 150 bridges with the height of 133 m or more and average age of 59 years which cannot be inspected by UASs. Again, a waiver is likely possible to relax this restriction.

5 Synthesis of UAS Bridge Inspections and Future Needs

The previous sections have outlined applications of UASs in different fields, including bridge inspection, and discussed the current capabilities related to automated inspections (i.e., 3D modeling, damage detection, and controls). UAS-assisted bridge inspections have had success throughout the United States that have resulted in successful routine inspections of easily accessible locations when UASs had access to GPS, and autopilot features. The compiled literature on these topics is informative about the future path of UASs for bridge inspection by recognition of current challenges and benefits. DOT research with UAS-based bridge inspections is relatively scarce and involved mostly off-the-shelf solutions and focused on feasibility. Proving that a UAS can be an alternative to visual inspections would very valuable in bridge inspection practice, but current studies have focused on case studies. This section compiles the current main benefits and drawbacks of UASs as an alternative to visual inspections and the future potential for automated inspections.

5.1 Immediate UAS Inspection Potential

As mentioned in Section 2.4, the most interesting aspect of using UASs for state DOTs and bridge inspection agencies were visual inspections. The following sections investigate the possible advantages of using UASs for bridge inspections.

5.1.1 Safer Inspection

One of the major advantages of UASs in this field is the higher degree of safety. According to the engineer of maintenance and operation at Michigan DOT, "…using UAVs provides a mechanism to keep the crew out of high risk situations" [100]. UASs can obtain photos from under-bridge regions without requiring manlifts and potentially road closures, allowing for increased inspector and public safety, while the acquired data by UASs have similar qualities as visual inspections [88]. Fig.5a shows a UAS during a targeted visual inspection to detect fatigue cracks. If an inspector was to perform the visual inspection (for location shown Fig.5a), it would require rappelling or a UBIT [46]. Fig.5b shows the inspection image of a possible fatigue crack taken by UAS. Inspection of high mast poles and cable-stayed members are other scenarios where UASs can provide a safer situation [15,110].

Additionally, safety risks and costs may decrease because there may be fewer people involved (Table 9). According to current FAA rules, having a certified pilot and a spotter is considered legally adequate to fly UASs; whereas, an inspection will typically involve at one to four people in the visual inspection.

(a)

(b)

Fig.5 (a) A UAS inspecting girders bridge under a bridge, (b) an image of a fatigue crack taken by a UAS from a bridge girder with fatigue crack

Table 9. Manual and drone cost comparison (adapted from [108])

Method of inspection	Time spent	Lane closure	People involved	Money spent
Visual Inspection	8hour	Yes	4	$4600 U.S.
UAS Inspection	1hour	Yes	2	$250 U.S.

5.1.2 Faster Inspection

The time required to inspect a complex bridge or obtain photos of a hard-to-reach location, like Fig.5, can be decreased considerably with UASs. For example, Yang et al. stated that it only took 42 minutes to complete an entire bridge inspection using a UAS: 25 minute set up time, 10 minute first flight, and 7 minute second flight. The inspected bridge was 240 m long and 8 m wide, but bridges are likely to be highly variable depending on the structure type [119]. In this case, public advertisement of the closure and set-up time for closing down the road can also be eliminated when the UAS is not visible to traffic. Note that the work by Yang et al. was a survey of the structure and was not of quality for a true inspection (i.e., detecting defects), which would take considerably longer. Table 9 is adapted from an AASHTO report, for deck inspection claiming UAS inspection reduce the deck inspection cost [108]. The size and condition of the inspected deck, and also the objective of this inspection were not mentioned in this report. Assuming both inspections were performed to get similar information of the deck, the UAS was faster by 8 times. There have been scenarios during the inspection where having a UAS sped up the inspection process, however, more comprehensive experiments and inspections need be carried out to determine when and how UASs can decrease the inspection time and by how much.

5.1.3 Economical Inspections

In addition to the safety and time reductions, there is also a documented cost reduction; many of the cost reductions are associated with the safety and time reductions. If UASs are used instead of manned inspection, cost for just the deck inspection can decrease from $4600 to $250 [108,123]. The itemized cost of the inspection, according the Dorsey, is shown in Table 9 [108]. This survey did not address many of the assumptions about costs associated with span length, age of the bridge, location of the bridge, etc. In addition, the current FAA regulation prohibits using UASs over the traffic, so the cost of lane closure, estimated to be $3,000, should also be added to the cost of UAS inspection. A more detailed study for under-bridge inspection showed a more realistic cost estimation for visual versus UAS-based inspection, as shown in Table 10 [120]. This table shows that the inspection costs of a two span bridge can be reduced by more than one third. However, there are hidden costs that are commonly ignored in these studies, such as cost of renting a pilot and UAS. For many DOTs, the inspection of a simple bridge (e.g., no fatigue details, relatively easy access, low traffic) may take only 20-30 minutes and require only a single inspector with a camera and binoculars [12]. In these cases, UAS bridge inspection will not improve the cost or time associated. For a large-scale bridge (2,400 m long), a 2017 cost analysis showed that UAS-inspection was 37% faster and 66% cheaper than the traditional inspection [88]. However, details regarding this calculation and inspection performance was neither reported or compared.

Table 10. The cost of visual and UAS inspections for under bridge (adapted [120])

Method of inspection	Cost of traffic control	Cost of UBIT	Cost of Inspectors	Total
Visual Inspection	$640	$2000	$1200	$3840
UAS Inspections	$320	0	$750	$1070

As a case study, a bridge with FCMs was inspected using hands-on and UAS-assisted methods. The bridge is located in Ashton, Idaho, and carries Ashton-Flagg Ranch road traffic over the Fall River (ITD Bridge Key 21105). The full details of this inspection can be found in [46,118]. The bridge consisted of two main longitudinal frames on the Northern and Southern sides (West-East orientation). Hands-on inspection was carried out using a UBIT in four hours to inspect the whole bridge. The total cost of the inspection was $391 per hour, including UBIT costs, of inspection ($1,564 for four hours) which is itemized in Table 11. Separately, a DJI Mavic Pro UAS was used to inspect the bridge. The UAS followed the water current without pilots control making inspection over the water impossible (refer to section 3.1.1, Idaho DOT, for more details). Due to this issue, only a quarter of the fatigue prone locations were inspected using UAS which included 12 susceptible connections in four floor beams, two girder splices, a girder web, a concrete barrier, and bottom flange two girders. The UAS-assisted inspection identified the presence of fatigue cracks in two floor beam connections. These cracks have previously been detected marked through hands-on inspections. The images from these fatigue cracks show the marker lines, but not the actual cracks (Fig. 6a). In addition, the UAS-assisted inspection ruled out the presence of fatigue cracks in other inspected regions (Fig. 6b). Other defects such as concrete delamination and efflorescence, and steel rust were detected in the UAS-assisted inspection. The UAS-assisted inspection took 4.5 hours with a net flight time of 1.5 hours (90 minutes). The inspection cost in this case was $200 per hour. Considering a quarter of the bridge was inspected in 4.5 hours, the inspection costs extrapolated to whole bridge using the UAS would be $1800. This case study shows the hourly cost of UAS inspection is almost half of the hourly cost of UBIT inspection, which agrees with previous studies [88, 120]. However, the extrapolated UAS inspection time was longer than the actual UBIT assisted hands-on inspection. The additional time made UAS-assisted inspection 15% more expensive than the hands-on inspection. It should be noted that the time and cost associated with using UASs is different for various situations as outlined in other places in this paper.

Table 11. The cost of hands-on and UAS-assisted inspections for FCM inspection [46]

Method of inspection	UBIT (per hour)	Support Truck (per hour)	UBIT Operator (per hour)	Inspector (per hour)	Pilot and UAS (per hour)	Total (per hour)	Full Bridge (total)
Hands-on Inspection	$200	$16	$75	$100	-	$391	$1564
UAS Inspections	-	-	-	$100	$100	$200	$1800

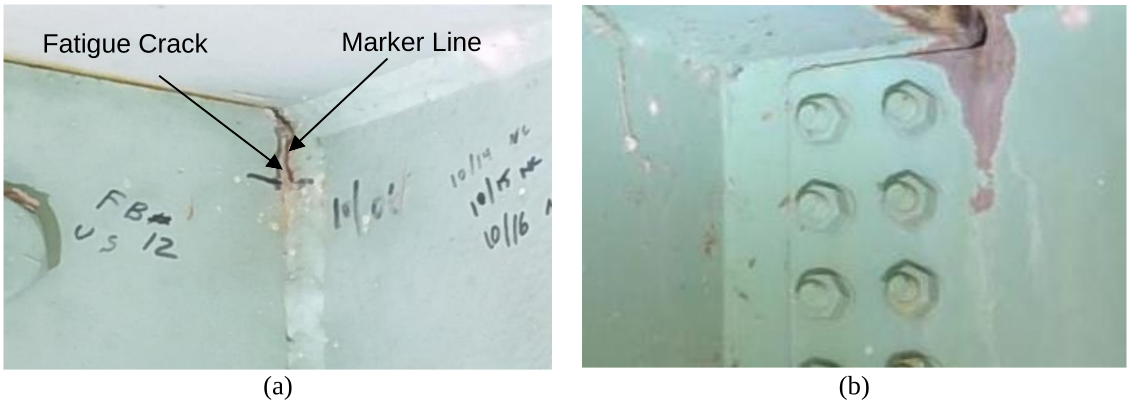

Fig.6 (a) UAS-assisted FCM inspection (a) a location with fatigue crack, (b) a location without fatigue crack

5.1.4 Other Benefits

An indirect benefit of UAS-assisted inspection may be lessened traffic congestion. Road closures and time required for a particular traffic disturbance can be limited, which is particularly important for high traffic bridges. Sometimes the objective of the inspection is to check the general integrity of the structure, such as checking if large items are missing or large areas are defected, for instance, a 330 m long barrier railing was inspected using a UAS in less than 3 hours, enabling to the designers to make an informed decision to ultimately replace the railing [88,110].

5.2 UAS Inspection Challenges

The advantages mentioned in section 5.1 are possible under relatively ideal conditions. Ideal conditions include a skilled pilot, no software and hardware malfunctions, an appropriate UAS, and no adverse weather conditions. Currently, there are many challenges associated with bridge inspections. Some challenges are due to the availability of this emerging technology, and some are due to the regulations associated with governing bodies such as the FAA and state DOTs.

5.2.1 Regulations

Current FAA restrictions are not too burdensome for an agency to perform inspections, but provide enough restrictions to limit use in some situations (refer to section 4.2). Regulations will relax over time, as in the past, as public perception, UAS reliability, and autonomous controls continue to improve. Currently, FAA regulations will allow UASs to inspect bridges if the they are not visible to traffic. Thus, for any inspection process that involves UASs being exposed to traffic, such as UAS bridge deck inspections, cable stay towers, above grade trusses, or even high mast luminaries, the traffic will need to be modified. Furthermore, FAA regulations mandate that the pilot is in visual contact with the UAS at all times, even if using first person view (FPV), which gives the pilot a live feed of the flight from a camera on the UAS. This mandate severely limits some difficult to access bridges which may still have inaccessible locations for the UAS due to this restriction.

5.2.2 Flight Control

Probably the largest hurdle to fully automated inspections is the GPS-denied environment under the bridge. Most pilots, skilled or unskilled, will have excessive difficulty without significant aid from the autopilot, the most useful and reliable of which comes from GPS signals. Coupled with the fact that most pilots own their own UASs, which will be used on multiple jobs, the risk of losing a UAS in a waterway or simply crashing it may deter many pilots from under-bridge inspections. UASs rely on GPS signals for autopilot features and stability. Under a bridge, these signals are either very weak or non-existent and UASs cannot be controlled properly [15]. Thus, claiming that UASs are a feasible alternative to UBIT visual bridge inspections, as some studies have indicated, is not accurate [108,120]. Zink and Lovelace handled this issue by using high-definition cameras with zoom capabilities, but the applicability of these techniques is limited [15]. Many new off-the-shelf UASs have indicated that they have additional sensors (SONAR, LiDAR) that can aid in GPS-denied environments, but there is little proof of feasibility at this time for bridge inspection [15,88]. Without the benefit of GPS, control under a bridge is very limited, especially in high wind situations, risking catastrophic damage to the UAS and sensors and even posing a safety hazard to the pilot, inspector, spectators, and motorists. There are many promising control possibilities to automate the inspection process, like SLAM outlined above, but the harsh environment and difficult scenarios limit the current generation of UAS controls packages.

A skilled pilot is necessary, especially in a complicated situation like a bridge inspection where there are potentially harsh environments. Pilot needs to have substantial navigation skills to capture stable images while still be able to complete the inspection without imposing damage to the UAS. A skilled pilot can aid in a successful under or over-bridge inspection, and DOTs are likely to mandate some specific level of skill. Presence of a pilot (COA/333 or Part 107) is also legally mandatory for any type of non-recreational activity in the outdoors. Wages for an accomplished pilot can be considerable and variable. According to an informal survey of UAS pilots available in the authors' area, costs can be as high as $1200/day but as low as $650/day, plus travel expenses. Based on the above findings, there is a major need for improvements in the areas of UAS controls, navigation, and image processing in order to maintain effectiveness.

5.2.3 Time

If for a typical structure a typical inspector will only require 30 minutes of onsite time to arrive at an appropriate condition rating, a UAS inspection will need to meet or exceed this to become viable. Considerable time and money could be spent on data post-processing if thermal images are desired as well as any semi-automated damage detection. Inspectors need a way to arrive at a condition onsite and move onto the next bridge without creating an additional level of analysis. Part of this will come with future automation of the inspection process, but currently, image-processing techniques for damage detection and 3D modeling are not at the level required for even a semi-automated real-time inspection. Whether for image modifications like removing image distortion or for intelligent feature detection algorithms like image-based crack detection, the post-processing operations have been commonly used for UAS bridge inspection research, but are still not time or cost effective for most bridges at this time [100,117]. Performing these complex operations is costly and requires professional and highly trained staff, which are inaccessible to most DOTs [110]. Post-processing operations also need time to perform on the order of a few minutes to a few hours. As such, there is a major need for automated or semi-automated tool development for bridge inspection that will make UAS bridge inspections feasible.

5.2.4 Weather

Weather will continue to play a major role in UAS bridge inspections. Unfortunately, if there is a bad weather day, an inspection cannot always be rescheduled due to the many demands placed on a bridge inspection program. Inspections are often scheduled many months out without the possibility of returning due to tight DOT and private inspector schedules, although inspection dates can become more flexible when a UBIT is not involved. The quality of the UAS flight and the acquired data can decrease due to adverse weather [102,117]; furthermore, captured images or videos may not be clear due to the variable lighting conditions underneath a bridge. High wind speeds will significantly increase the allowable clearance between the UASs and the object of interest because of the risk for damaging sensitive mechanical equipment or even the structure itself [110,118]. UASs have several vulnerable components, especially the propellers, but also sensors. The pilot needs to be very cautious near a structure while trying to obtain the best resolution possible, and the complex geometry of bridge structures further complicates the situation. Many newer commercial UASs contain some obstacle avoidance software integrated into the autopilot; however, these options have not been evaluated in any known research. These options have the potential to help, but depending on the settings they could also hinder the inspection if the UAS gets too close to a point of interest [46]. One of the greatest tools a UAS pilot or spotter has for real-time defect detection is live streaming of visual data to the ground crew. However, due to the distance from the UAS to the receiver, interference, and bad weather, this can be compromised, making post-processing mandatory [46]. For a smaller bridge, a setback like this can eliminate the time and cost benefits of using UASs for inspections.

5.2.5 Functionality

UAS inspections can only replace visual inspections and are unlikely to be able to perform physical inspections anytime in the foreseeable future, but UASs can perform some limited NDE. Many times during an inspection, an inspector must remove rust, nests or droppings from an area to observe a defect. UASs cannot prepare the surface for defect detection without major advances in robotics and control. UASs are limited to non-contact NDE methods (e.g., visual, thermal) to assess the condition, whereas with a UBIT inspection, nearly all options for bridge inspection are available. Currently, an inspector can measure the size of a defect in real time, whereas a UAS can only provide this function on a limited basis with additional sensors and significant post-processing, most of which would not be off-the-shelf. The application of UASs are restricted to visual inspection, and if the inspectors decide a region requires more investigation, a UBIT must be used, which may still allow for a more robust inspection and cost reduction.

A functional UAS requires constant tuning and maintenance on the platform and all the components, e.g., motors, propellers, sensors, ground station unites, and controlling joy sticks [110]. UASs require skilled mechanical and electrical engineers to retune their system after replacing or upgrading a broken or out-of-date component. Without proper tuning, the autopilot functions can be less effective, resulting in less effective or dangerous inspections. However, the cost of individual components on UASs are continuously decreasing. Even full off-the-shelf system costs are rapidly dropping while their functionality are improving.

5.2.6 Gaps in Industry

To select a suitable UAS for inspection, one needs to consider various parameters. For bridge inspection these parameters are varied based on inspection type and owner needs [46,118]. If the bridge inspection industry wishes to move in the direction of UAS assisted inspections for the long term, these needs must be formalized and this paper is a first step to this.

The bridge inspection programs for each state can be very different. Each state relies on a combination of consultants and state employees to perform their required bridge inspections. Many consultants, eager to win more business, are pressing DOTs to allow UAS-assisted inspections. DOTs are grappling with this change and desire to develop standards and training protocols to ensure inspection quality. The recent popularity of UAS in civil infrastructure health monitoring and inspection has created the opportunity for private companies to perform UAS-based inspection professionally. AETOS, Empire Unmanned, Microdrones, BDI and TechCorr are among companies providing UAS-based inspection services; however, bridge owners are not usually among their clients. Most of the inspections conducted by these companies have been on tanks, pipe and power lines, and industrial sites (e.g. power plants) which are not as complicated as bridge inspections. DOTs may wish to train internal UAS pilots for bridge inspection. As of 2018, the cost of UAS registration for commercial UAS is $25. The pilot has to obtain a remote pilot license which costs $165. The pilot can acquire field-training through academic aviation credits (e.g., $500 at Utah State University for one semester). The cost of UAS varies from $500 to several thousand dollars; however, a DJI Mavic Pro, or a DJI Mavic Air are around $1,000 and are suitable for bridge inspections. For a DOT, the total cost for training an employee as a UAS pilot can be as low as $2,000.

5.3 Future Needs

This paper has outlined several current capabilities and proof of concept investigations for UAS bridge inspections as well as shortcomings of using UASs and areas in need of improvement. The following section outlines the areas of improvement that will enhance the capabilities of UASs and improve and automate infrastructure inspection.

5.3.1 Autonomous Control

Overall, each study which investigated unmanned inspections, whether bridge inspections or another application, used some form of autonomous control. Equipping the platform with some form of autonomous control algorithm(s) and appropriate sensors such as cameras (with image processing), LiDAR, and SONAR can help the UAS to autonomously record or avoid features or even simply hold altitude in GPS-denied environments; this would vastly improve bridge inspections. Some of these features are being implemented to various extents on a smaller scale in next-generation off-the-shelf platforms [15,46,118]. However, current limitations on UAS autonomous control ties the flight and inspection performance to the skills of the pilot. If fully autonomous control is to ever be achieved, the UASs can be operated by the bridge inspectors themselves, assuming FAA regulations allow it.

Additionally, in order to have widespread augmentation of human inspections, the inspection of all bridge types must improve, posing cost, time, and sensing challenges. Self-navigated UASs are the solution for achieving more efficient and reliable bridge inspection; however, no studies have been carried out to assess the feasibility of self-navigated UASs in bridge inspection. However, the breakthroughs in UAS technology have made them considerably more functional. For instance, the size and weight of UASs and sensors have been decreasing while the allowable altitude, control range, and payload capacity are increasing.

5.3.2 Sensors

Visual and thermal cameras are the most common UAS sensors available for inspection purposes. These technologies still provide significant opportunities in the field of 3D modeling and defect detection. However, UASs are severely limited to non-contact only sensors, eliminating the most popular and proven NDE technologies with which bridge owners are comfortable. Improvements are occurring rapidly in non-contact sensing like infrared thermography and high resolution visual imagery; however, these are not well used or accepted by DOTs [31, 46,72,104,102]. Probably the most difficult hurdle to improving sensing of bridge structures is widespread acceptance of non-contact NDE by DOT engineers. This will likely require significant research to improve accessibility, training, and political improvements for this conservative group of engineers. Image processing techniques, specifically those in the thermography area, have shown promising results. These results are mostly validated in the laboratory, but not in the challenging environments in which bridges reside [46,85,87,117,121,122]. One major area of impact for UAS bridge inspection will be FCM inspections, which require a disproportionate amount of the operations and maintenance budget. FCM inspections are usually manned, arms-length inspection that uses some form of contact NDE along with a UBIT. The FCM inspections are often done on a large structure and are exceptionally expensive [118]; however, UAS based inspection are not as successful as hand-on inspections in finding fatigue cracks (often much less than 0.5 mm wide) [46,117,118]. In addition, UAS-assisted FCM inspections are required to have some sort of self-navigation for GPS-denied operations which has not been resolved yet [46,118].

5.3.3 3D Model Reconstruction

Many previous studies illustrated the possibility of creating 3D models of a bridge from UAS-captured images. The ability to create a 3D model that includes enough detail to observe defects, support settlement, or structural members displacements could be invaluable to bridge management engineers. However, with off-the-shelf software and with current algorithms this is very time-consuming, not accurate enough, and not at a high enough resolution (see Section 2.6). With the improvement of LiDAR and even SONAR sensors, 3D models can also be constructed from LiDAR information, but only with skilled post-processing. There is potential for this with current sensor fusion techniques that combine several types of information, increased functionality, and accuracy [124-126]. With current inspection requirements, 3D models may be redundant for the average bridge, which takes only 30 minutes to inspect, but future work may make them more feasible and useful. Combining a 3D reconstructed model with Bridge Information Modeling may prove to be highly valuable, especially for older structures that do not have plans or need a detailed load or condition rating [127].

In addition to a detailed model suitable for inspection, an accurate model would be a major step toward autonomous inspections and self-navigated UASs. The SIFT and SURF algorithms have proven to be the most efficient way for feature detection in the realm of 3D reconstruction; however, it is expected that the future focus of visual sensing should be on generating efficient algorithms for real-time 3D model reconstruction that align with DOT inspection needs.

5.3.4 Automatic Damage Detection

There are several ways damage can be detected using a UAS-assisted inspection. The simplest way is to have a trained inspector view a live feed of video during the inspection and manually identify damage as if the inspector was near the damage. This option works well but is limited by the quality of the view-screen, which is limited to 1080p resolution, or in some cases, 4k resolution. Furthermore, this style of inspection is hampered by inspector bias and human error. As many other industries attempt to limit human inspections, it is likely that human influence will eventually be reduced through some form of augmented or automated damage detection. Currently, a significant issue with autonomous damage detection is the expense of post processing. Some recent techniques have been developed that can provide a near real-time augmentation for crack detection, but more robust tools are needed that fit within the current inspection framework [72]. If additional sensors are employed, like LiDAR or thermal imaging, damage detection techniques will require a skilled investigator to evaluate for accuracy and/or very generic algorithms need to be developed [66]. A normal human inspection results in a handful of images that are used for record keeping purposes while UAS inspections result in thousands of images, increasing storage demand, and off-site inspector time, which is unlikely to reduce costs.

Furthermore, the accuracy of all damage detection techniques depends on the quality of the raw data, which is unlikely to be recollected if post-processing must be done off site. Because adverse weather and vibration of the platform can cause blurry images, shadow contrast, and lack of observable heat flux, care must be taken to use the appropriate sensor and platform for the situation. More intelligent post-processing algorithms used to detect smaller defects are also in demand but will always be tied to the raw data accuracy. The ability to automatically detect and separate irrelevant objects in the images, such as shadows and background scenery lines, is a current hot topic in crack detection algorithms. In the case of thermal imagery, it is important to select a proper time to capture thermal images. The proper time depends on the depth of the defects, the material, and the weather temperature [128,129]. More sensitive and higher resolution thermal cameras can help, but good thermal measurements are more likely to be affected by how the inspector pre-planned the inspection process. It is anticipated that more standard procedures, like ASTM D4788-03, which focuses on bridge deck delamination detection using thermography, will be developed for surface and subsurface defects and for various materials in the future [31].

5.3.5 Regulation

Current rules that apply to UASs are much more relaxed than in the past, but still represent significant restrictions. Since the applications of UASs in structural inspection and maintenance are being developed in conjunction with government agencies (state DOTs), more flexible regulations are predicted to be sanctioned in the near future. These new regulations will likely reflect public perception of UAS safety as well as the improvements on UAS control and platform reliability. With respect to infrastructure inspection, the rules that hinder inspection the most are the visual line-of-sight necessity, required visual observers, and limit of a single UAS controlled by a single pilot.

6 Available UASs for Bridge Inspections

In this section, available off-the-shelf UAS platforms are presented with their suitability for different types of bridge inspections. The recommended UASs in this section are based on the authors experience and do not represent the whole UAS market. Due to lack of definitive guidelines to help with the selection of UASs, sensors, and other equipment, this can be challenging for DOTs to successfully start a UAS inspection program. Table 12 shows several UASs along with their general specifications, price (as of April 2018), and the potential bridge inspection applications. The price of a UAS for bridge inspection varies significantly, depending on the purpose of the inspection, quality and quantity of the integrated sensors, and computing capabilities. Integrating thermal cameras with the existing visual sensors can increase the price of the UAS up to three times. If a requirement of inspection is 3D model reconstruction, the size and the price of the UAS increases dramatically. Neither of these options may be necessary to complete most types of bridge inspection. On the other hand, in the case of under-bridge inspections, the UAS must have an auxiliary positioning system, vision system, to compensate with lack of GPS signals, in order to have a successful mission. The potential applications mentioned in this table are not without the limitations and challenges discussed throughout this paper; however, the content of this table guides the bridge owners and inspectors when purchasing a UAS and provides a variety of commercial options. Furthermore, the table does not suggest that the entire bridge inspection can be performed using only the recommended UASs. The possible challenges during each UAS bridge inspection are expected to vary significantly since published inspection reports with UASs are limited.

Table 12. General specifications for UAS-assisted bridge inspections

UAS	Sensors	Positioning System	Size (cm)	Maximum Flight Time (min)	Price Range ($)	Potential Bridge Inspection Applications
Parrot BEBOP 2	Visual	GPS	32.8 by 38.2	25	500-700	Over-bridge, visual detection of macroscale surface cracks (thicker than 0.8 mm), routine inspection, checking the bridge structural integrity
3DR Iris[1]	Visual	GPS	63 by 38	20	600-800	
3DR Solo[1]	Visual	GPS	40 by 40	20	800-1000	
DJI Mavic Air	Visual	GPS, Vision System	21.3 (diagonal)	20	800-900	Over and under-bridge, visual detection of surface cracks (as thin as 0.04 mm), routine inspection, FCM inspection, checking the bridge structural integrity
DJI Mavic Pro	Visual	GPS, Vision System	33.5 (diagonal)	27	1000-1200	
DJI Phantom 4 Pro	Visual	GPS and Vision System	35 (diagonal)	30	1800-2000	
	Visual and Thermal				5500-8000	Over and under-bridge, visual detection of surface cracks (as thin as 0.04 mm), subsurface defect detection (delamination), routine inspection, FCM inspection, checking the bridge structural integrity
DJI Mavic Air	Visual and Thermal	GPS, Vision System	21.3 (diagonal	20	4000-6000	
DSLR Pros Law Enforcement	Visual and Thermal	GPS and Vision System	64.3 (diagonal)	17	13000-15000	
Albris SenseFly	Visual and Thermal	GPS	56 by 80	20	30000-35000	Over-bridge inspection, autonomous 3D model reconstruction, microscale defect detection (thinner than 0.02 mm),
Altus LRX	Visual, Thermal, LiDAR	GPS	140 (diagonal)	20	40000-50000	Over and under-bridge inspection, autonomous 3D model reconstruction, microscale defect detection (thinner than 0.02 mm), subsurface defect detection

[1] No integrated camera

7 Conclusions

This paper has outlined the state-of-the-art for bridge inspections and UAS technology with the aim of educating and informing academics and decision makers about the current and future capabilities of UAS-assisted or automated bridge inspections. The current state of practice for bridge inspections, especially in United States, is heavily tied to visual inspections with minimal use of NDE. Bridge owners have demonstrated reluctance to accept NDE methods unless they are absolutely required for bridge evaluations. UAS-assisted bridge inspections have the potential to not only decrease costs, but to also improve the adoption of NDE technologies, potentially increasing inspection accuracy, however UAS inspections face major hurdles.

UASs have shown promising results in civilian applications as well as civil engineering purposes, and many state DOTs have performed feasibility studies and found significant limitations, but also successes. The most common UAS applications in DOTs were traffic monitoring and surveillance, road condition assessment, and mapping; however, significant effort has been put into bridge structure inspection with varying degrees of success. The perception of UAS effectiveness for bridge inspection is tied to several variables, including DOT expectations, pilot skill, weather condition, and off-the-shelf limitations. It was shown that, ideally, UASs can provide less expensive and less time-consuming inspections for under bridge regions without traffic closure, but not in all situations and there are obstacles to overcome. FAA regulations have recently relaxed, but impose significant limitations, including required line of sight and UAS certification. Using advanced NDE sensors or even visual images can become too burdensome to be effective for routine inspections. Current autopilot controls have become a severe limitation for under bridge inspections due to the loss of GPS signals, causing a UAS to rely on a vision positioning system or a suite of other sensors which are questionably useful in the severe under-bridge environment.

The literature identified two major potential functions for UAS based inspections: 3D model reconstruction and autonomous damage identification. Unfortunately, these functions face major implementation limitations in order to be functional for complex – or even routine – inspections. Programs capable of generating 3D reconstructed bridge models, from either SFM or MVS, using feature detectors and feature descriptors such as SIFT and SURF have been used for 3D model reconstructions of building, sites, and objects, but are very time consuming and require highly skilled technicians. These models have promising applications for UAS navigation but are unlikely to be accurate enough for bridge inspections without significant advancements. Autonomous defect detection methods are another promising advantage for UAS-assisted bridge inspections. Surface defect detection, for example, cracks, spalls, and surface degradation, have been successfully detected from visual images. Delaminated regions have been located and measured using thermal imagery on concrete bridge decks. A major hurdle to the adoption of these methods for UAS bridge inspection is resistance from bridge owners that have historically not implemented NDE technologies.

Based on the synthesis of this state-of-the-art review of bridge inspection and UASs, the following conclusions can be made:

1. The review of current bridge inspection practices makes it clear that there is a need for continuous improvement of bridge inspection procedures and cost reductions. Several NDE technologies were identified that can provide a better inspection but, based on DOT surveys, may not be worth the time, effort, post-processing, and cost associated with them [46,124]. UAS sensors may also fall within this category. Improvements should take the form of reduced inspection time and increased inspector and public safety, as well as decreased inspection costs, all of which indicate the need for automated inspections [27]. If automated inspection processes are going to replace standard practice, then they must be robust and require a similar amount time and effort to current bridge inspections techniques in order to gain widespread adoption.
2. The recent advances of UASs and UAS have the potential to shift the bridge inspection paradigm by providing low cost options to gather previously difficult or expensive images [108,120,].
3. UASs have increased in popularity and functionality for many applications, but the challenging nature of bridge inspections has reduced their effectiveness in this area [15,28,41,46]. UASs can also decrease the allocated time and budget for large-scale bridge inspections by providing inspection data comparable to hands-on method [88,117,118].
4. There have been mixed successes for UAS-assisted bridge inspections throughout the United States that have resulted in successful inspections of easily accessible locations where the UAS has access to GPS, the most reliable and effective tool for UAS autopilots (see Table 5).
5. There is a major need for improvements in the areas of UAS controls, navigation, and image processing in order to maintain effectiveness [46,100,110].
6. Weather currently plays too big of a role in UAS flight success, which is a very significant barrier for many state agencies with very tight inspection schedules [46,110,102]. This can be mitigated with continued

improvement of autopilot controls in GPS-denied environments. UAS controls need to improve such that a pilot can safely and effectively obtain stable images of every part of the bridge in any reasonable weather.

7. For UAS inspections to become commonplace and cost-effective, automated inspection may need to become a reality, or at least, vast improvements will need to be made on autopilot controls [41,43,44,97]. Based on the above syntheses, full automation during a bridge inspection is not possible given current technology and environmental challenges.
8. Image processing techniques (3D mapping or damage detection) that can detect defects are a significant advantage of a UAS inspection [107,131], but without the possibility of a real-time inspection will not become a routine part of any bridge inspection soon due to the level of detail required [46,118].
9. Bridge owners must learn to accept and become comfortable with the non-contact NDE techniques unique to UAS inspections for the full potential of UAS bridge inspection to be realized [8,129]. This places the burden on industry and researchers to develop accurate, generic algorithms for post-processing that can facilitate a real-time inspection or fit within existing local bridge inspection constraints [55,69,70,71].
10. Current FAA restrictions are not too burdensome for an agency to perform some inspections, but provide significant challenges to be useful in all situations [46,110]. Regulations will relax over time, as public perception, UAS reliability, and autonomous controls continue to improve [44,46,110].

8 References

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