Applications of UAVs in Civil Infrastructure

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Abstract: Unmanned aerial vehicles (UAV), or drones, have become popular tools for practitioners and researchers alike. Recent years have seen a significant increase in UAV uses for many applications in the fields of science and engineering. A broad array of research development in UAVs has been reported in the literature. This paper provides a summary review of efforts related to UAV development with a focus on civil infrastructure applications. First, guidance is provided for researchers looking to newly incorporate UAVs into their research efforts. The advantages and disadvantages between different UAV types are outlined and performance characteristics discussed. Examples of different sensor payloads that demonstrate expanded functionality are provided. The review also provides an overview of research efforts in the emerging domain of wireless sensor networks and data processing algorithms specific to UAV-collected data. Highlights of recent achievements of UAVs in post-disaster reconnaissance, infrastructure component monitoring, geotechnical engineering, and construction management are presented. Lessons learned from UAV implementation and considerations for good practice are also discussed. The paper concludes with a discussion of the emerging and future research domains that address the most pressing knowledge gaps in current practice.
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Introduction

Unmanned aerial vehicles (UAVs), also commonly termed drones, are aeronautical platforms that operate without the use of onboard human operators. Recently, UAVs have been the focus of both significant praise and criticism. Media coverage has primarily driven the dialogue on UAVs in the public sphere. From this perspective, the focus has largely been related to their use in military operations (BBC 2012; Mazzetti 2012; Syed 2012; Savage 2016). UAV technology is much more advanced in the military sector than other sectors and has seen about a century of development. For example, the Kettering Bug, a self-flying torpedo, was developed in the United States (US) but never used in combat (Stamp 2013). Radio-controlled aircraft were used by the British military for target practice before World War II. Also during World War II, US and German militaries used radio-controlled aircrafts to fly into heavily fortified targets (Connor 2014). Additionally, pulse-jet UAVs based on German Vergeltungswaffe Eins (V-1) cruise missiles were developed in the US and France following the war for target practice (Winter 2000). Outside of the military sector, UAVs have also been used for decades by public entities, such as police and fire departments, in North American cities and this use is currently expanding (Nguyen 2014; Mangione 2015; FAA 2016; Rojas 2016). More recently, the commercial sector has explored UAVs for use in their businesses (Syed 2012; Nguyen 2014; Boucher 2015). In fact, many of the UAVs originally developed for military purposes are now being used for civilian applications (Syed 2012; Boucher 2015).

In the early 2000s, the public began to show greater interest in UAV technologies due to reductions in UAV costs and the availability of more functional platforms. In response to the broad proliferation of interest in the US, the Federal Aviation Administration (FAA) initiated a small unmanned aerial vehicle registration program in December 2015. During the first 30 days of this program, nearly 300,000 individual owners registered their personal UAVs (FAA 2016). Regulations in the US imposed by the FAA have been met with some criticism and have created a debate over how extensively UAVs should be used in the national airspace system. Outside of the US, UAV regulations vary widely from country to country, or may not even exist. Despite scientific and regulatory hurdles, many scientific and engineering communities have also delved into UAV technology development or incorporated UAVs into their respective fields. Some industries (e.g., precision agriculture) have fully incorporated UAVs, making them an integral part of their state of practice. Other fields (e.g., geotechnical and structural engineering) have only begun to explore the potential of UAVs but their impact is already evident as discussed in this review.

Given the rapid growth of interest in UAV technology, this review aims to present a broad overview of UAV technology and how it is being adopted in the field of civil engineering. Emphasis is placed on the most recent technological advancements and on the breadth of applications UAVs have in the field of civil engineering while highlighting the research challenges that remain.

Structure of the Review

The section "Unmanned Aerial Vehicle Platforms" provides a fundamental overview of UAVs and discusses the pros and cons of different platform types. In this section, basic guidance is provided to readers interested in implementing UAVs for their own applications. To frame this guidance, the details of several popular commercial platforms are provided. This section is primarily geared toward

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researchers looking to begin UAV integration with their work. It should be noted that the UAV platforms reported on herein are likely to rapidly change following this review; however, the fundamental principles presented will remain. The next section "UAV-Deployed Sensors" presents examples of the ever-growing set of sensor payloads that can be carried by UAVs. Due to their promise, the greatest emphasis (excluding optical cameras) is placed on UAV-based light detection and ranging (LiDAR) systems. The comparable nature of LiDAR- and image-derived point clouds is also covered. The section "System Integration and Data Processing Challenges" provides an overview of UAV integration with high-level systems such as wireless sensor networks (WSN). The challenges associated with interpreting data collected by UAVs and combining it with other data sources is discussed. The next section "UAV Applications in Civil Infrastructure Systems" summarizes recent examples of UAVs applied to broad research domains of civil infrastructure including post-disaster reconnaissance, monitoring of critical infrastructure components, construction progress monitoring, and geotechnical engineering. The authors of this paper consider these broad domains to contain the most cutting-edge advancements in topics relevant to civil infrastructure systems.

The final section "Lessons Learned and Considerations for UAV-Based Infrastructure Investigations" contains a discussion of infrastructure-specific considerations for UAV-based data collection and inspections. Some lessons learned and key considerations based on the authors' experiences are also provided. It should be noted that this review is not intended to serve as an exhaustive compilation of all applications of UAVs in civil infrastructure systems; rather, the paper aims to present representative research efforts that highlight the transformative impact UAVs can have when applied in the field.

Unmanned Aerial Vehicle Platforms

When introducing UAV-related engineering literature, it is important to define some key terms. UAV is defined as an aircraft that operates without an onboard human. Unmanned aircraft system (UAS) is defined as the UAV platform in addition to communication, piloting, sensing, flight planning, and other critical components needed for UAV operation. UAS is a much broader term describing the entire system that enables UAV operations. The terms UAV and UAS are closely related, and readers of engineering literature may find them used interchangeably; however, the distinction should be made. Thorough discussion of an UAV-related topic cannot be made without reference to the relevant UAS components. Remotely operated UAVs are actively controlled by a pilot. Autonomous UAVs perform functions without active human involvement. However, varying degrees of automation will appear in most modern UAS. For example, an UAV may be remotely operated by a pilot, but may use automation to maintain its position in the absence of commands from the pilot. The relative autonomy of a specific platform will also depend on the software used. Both manufacturer-included and third-party software packages offer a variety of options for automating functions (e.g., image capture, stabilization, flight path routing, and landing).

For the purposes of this paper, the FAA definition of small UAVs as those weighing less than 25 kg (55 lbs) is adopted (DOT 2016). In fact, the vast majority of the applications identified in this paper use small UAVs with most weighing less than 4.5 kg (10 lbs). UAVs can generally be divided into three types: fixed-wing, rotorcraft, and vertical takeoff and landing (VTOL) vehicles. Fixed-wing UAVs fly similarly to a traditional aircraft, and airframes can vary just as much as traditional aircraft. Helicopters use one rotating propeller attached to the main body, while multirotor UAVs are propelled by multiple rotating propellers attached to arms extending from the UAV body. VTOL UAVs can be considered as a combination of multirotor and fixed-wing UAV designs (Byun et al. 2016). These platforms lift off the ground vertically, as a multirotor platform does, but then fly horizontally with fixed wings after takeoff. There are few VTOL UAVs commercially available and the platform type still under development. Examples of the different aircraft types are shown in Fig. 1. Blimps and balloons have also been used as airborne sensing systems; however, they have a limited scope and have not been at the forefront of current research. Balloon platforms are most useful when sensors need to remain airborne and stationary for long durations. Take et al. (2007) used a helium-filled airship to monitor thermal expansion and wrinkling of exposed geomembrane landfill liners. More discussion of blimps and balloons in transportation engineering can be found in Brooks et al. (2014).

Each type of UAV has advantages and disadvantages that, depending on the application, may be more or less critical. In general, fixed-wing flight is much more efficient in covering large areas. Hence, fixed-wing UAVs are generally used to cover large distances rapidly and are ideal for mapping applications or kilometer-scale measurements. Multirotor UAVs have flexible mobility and the ability to hold their position and rotate. They are ideal for applications requiring precise vehicle placement and mapping of complex three-dimensional (3D) features. UAV platform types can be broken down further on the basis of wing or rotor geometries. Fig. 2 shows a more detailed breakdown of UAV platform types. Fixed-wing UAVs can be constructed with as many wing geometries as traditional aircraft can (e.g., bi-planes or tri-planes). However, for the purposes of this discussion, fixed-wing UAVs are divided into three generalized wing orientations (and not by the number of wings). Straight-wing UAVs appear as prototypical model airplanes. The wings protrude perpendicularly from the sides of the aircraft body. The wings can have a variety of shapes in plan view, such as elliptical, but are typically rectangular. Straight-wing alignments allow for good flight control at lower speeds. Swept-wing UAVs appear similar to straight-wing UAVs, but the wings are angled

(a) (b) (c)

Fig. 1. Examples of some commercial UAVs: (a) fixed-wing senseFly eBee (reprinted from Sensefly 2015, with permission); (b) multirotor DJI Inspire 1 (reprinted from DJI 2016, with permission); and (c) VTOL FireFly 6 (reprinted from BirdsEyeView Aerobotics 2016, with permission).

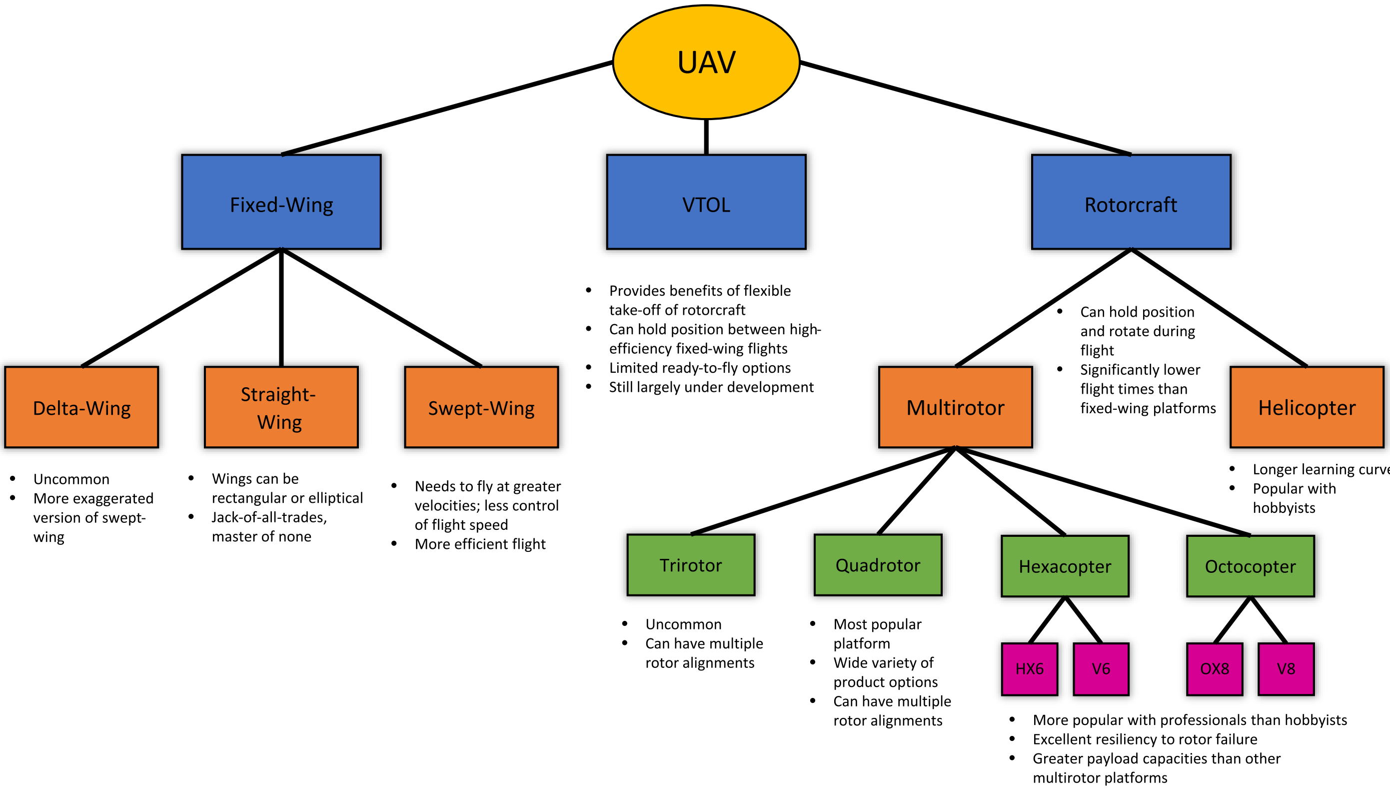

Fig. 2. Hierarchical taxonomy of UAV platform types.

(i.e., swept) toward the tail of the aircraft. The senseFly eBee shown in Fig. 1(a) is an example of the swept-wing alignment. Swept-wing UAVs allow for greater flight efficiency relative to straight-wing UAVs but must maintain higher velocities making them less maneuverable than their straight-wing counterparts. Delta-wing UAVs are an exaggerated version of the swept-wing alignment. In plan view, the aircraft is shaped similarly to an isosceles triangle. The pros and cons of this wing alignment are the same as the swept wing, but more exaggerated.

The types of UAV rotorcraft platforms are defined by the number and alignment of the rotors. There are two distinct types of rotorcraft: helicopters and multirotors. Helicopters have a single overhead rotor and long tail containing a small rotor in an orthogonal plane for stabilizing and adjusting heading. Helicopters are popular with model aircraft hobbyists and offer less flexibility for use in civil engineering applications. Due to being more difficult to fly manually, they tend to have a steeper learning curve than multirotor platforms for novice users. Multirotors offer shallow learning curves and are easier to control in space. However, they are comparatively more complex in terms of their development. In Fig. 3, multirotor platforms with three, four, six, and eight rotors are identified; these platforms are singled out because they are the most popular. Obviously, a multirotor platform with any number of rotors in a variety of alignments could be developed. A general rule of thumb is the more rotors the UAV has, the more lift capacity it has. In addition, more motors offer increased flight stability, making them easier to control, and offer some redundancy in the case of motor failure. An UAV with six or more rotors may have the ability to remain airborne or make an emergency landing if motor failure occurs. Trirotor and quadrotors do not offer redundancy and will crash upon failure of a single motor. The cost of the UAV platform also roughly scales with the number of rotors due to the need to buy more motors and larger batteries.

Trirotor platforms typically have three rotors attached to arms either 120° apart (Y-configuration) or 90°–180° apart (T-configuration). While inexpensive, these platforms are less stable and have low lift capacities due to the small number of rotors. Quadrotor platforms are by far the most popular and have been shown to be flexible platforms with fewer moving parts than hexarotors and octorotors. The quadrotor mounts the rotors to four arms each 90° apart; to balance the frame in flight, two opposite rotors (180° apart) rotate in a clockwise direction while the other two rotors rotate counterclockwise (X-4 configuration). With only four arms, quadrotors can be constructed to a small diameter making them ideal for casual hobbyists. The reliability and subsequent popularity of commercial quadrotor platforms has also resulted in them being viewed as the iconic multirotor design.

Hexarotors come in two frame types: either in a Y-rotor frame with arms 120° apart or in a HX-6 configuration which consists of six arms 60° apart. The Y-configuration includes two rotors on each arm and is referred to as a Y-6 configuration. As with all configurations using stacked motors, the top and bottom rotors rotate in opposite directions (clockwise and counterclockwise). In the HX-6, the rotors alternate between clockwise and counterclockwise. Octorotor platforms have two configuration types: OX-8 configuration or a classical X-8 configuration. The OX-8 configuration consists of eight arms each 45° apart with rotors alternating between clockwise and counterclockwise motion. The classical X-8 consists of four arms 90° apart with each arm supporting two rotors rotating in opposite directions. In general, the X-8 and Y-6 configurations are resilient in the face of rotor failure. Stacking two rotors on each arm in the X-8 and Y-6 configurations reduces their flight efficiency due to each rotor disturbing the air surrounding the other rotor. Stacked rotors can be beneficial because they reduce the number of arms on the aircraft, greatly reducing the total weight.

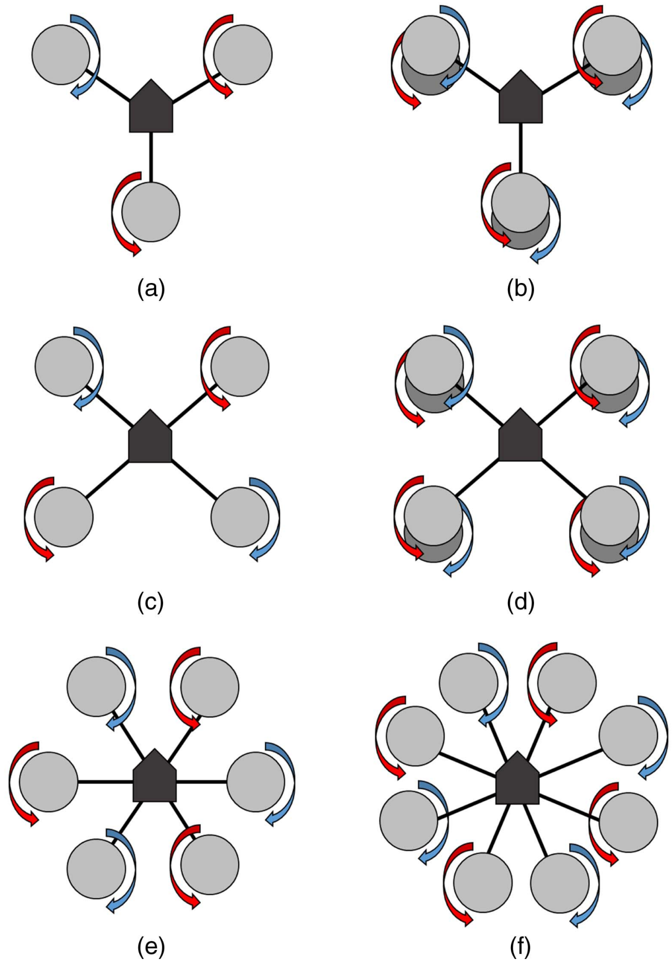

Fig. 3. Common multirotor layouts: (a) Y-3 trirotor; (b) Y-6 hexarotor; (c) X-4 quadrotor; (d) X-8 octorotor; (e) HX-6 hexarotor; and (f) OX-8 octorotor.

Reducing the base weight of the UAV has a significant effect on flight time and allows larger payloads to be carried. In general, hexarotors or octorotors are used to lift heavy payloads such as multicamera systems and other expensive sensors. Fig. 3 illustrates some of the most popular multirotor layouts.

Year to year, technology improvements have made UAVs more functionally rich while their costs have continued to decrease. Specifics on the cost of individual platforms is not provided because costs change rapidly and are typically tied to integration of the latest technological innovations. The cost of new commercial small UAVs varies widely from less than USD 50 for a low-definition camera quadrotor to USD 50,000 or more for a highly specialized multirotor platform. Additional technology advancements increase the cost of multirotor UAVs such as multisensor obstacle avoidance and real-time kinematic (RTK) GPS add-ons which may cost several thousand dollars. Other capabilities can significantly influence the cost of an UAV package including GPS-denied navigation, photo/video resolution and framerate, image processing software, and flight planning software. Platforms originally developed for military operations, such as the General Atomics Predator line, are available for long-range surveillance applications at great cost. However, these military-based UAV platforms have not found many uses in civil engineering because of their costs and due to the social complexities of integrating previously militarized UAV platforms into civilian applications (Boucher 2015).

The high demand for civilian UAVs has driven the market to provide a wide range of options available at many price levels. The range of UAV costs is dictated by how specialized the UAV platform is including the following performance attributes: vehicle type (multirotor versus fixed wing), position accuracy, permissible payload, maximum flight time, sensor compatibility, flight controller, onboard data processing capabilities, and closed- versus open-source software framework. The relative importance of these performance characteristics will depend on the specific application. Accurate and stable positioning is critical when movement leads to increased sensor measurement error or when the UAV must be close to the object of interest. For example, for inspecting bridges and rock structures, the UAV must be able to resist abrupt changes in wind speed while conducting close-range inspections. In general, maximizing flight time is important for any application and is primarily controlled by the UAV payload and battery configuration. The flight time required for surveying applications is a function of camera resolution and desired survey quality. For a given required image resolution of the target, a higher resolution camera can collect the images from a greater altitude and therefore fly along a shorter flight path. Table 1 summarizes some basic performance attributes reported by manufacturers for a range of currently available low-cost commercial UAV solutions. Many of the platforms identified in Table 1 have integrated cameras. The resolution of the photos and videos recorded by the cameras varies widely and can increase significantly between model generations. For example, between the DJI Phantom 3 Professional and the later generation DJI Phantom 4, the camera resolution increased from 12 to 20 MP. For platforms without integrated cameras, the user can select a camera with the desired resolution. State-of-the-art digital cameras can be carried as long as payload limitations are met.

In Table 1, the weight for each UAV is the out-of-the-box base weight or a typical flying weight for the platform. Each UAV can also carry a maximum takeoff weight that represents the base weight plus the weight of payloads. Hence, the maximum payload weight is the difference between the maximum takeoff weight and the base weight. In general, UAVs can carry a greater payload than identified by the manufacturer, which can be estimated by considering the maximum thrust of a multirotor's motors. When the maximum payload capacity of a platform is reached, it has a significant negative impact on flight performance including shorter flight time and potential instability. The eBee is a fixed-wing platform made of a lightweight foam material with both attributes contributing to a long flight time of 50 min. The hardware associated with octorotors and hexarotors make these UAVs the heaviest on the list. The provided flight times correspond to the reported platform weight. If the payload is reduced (when possible) for some of the platforms (e.g. Matrice 600) the flight time increases. Similarly, as payload is added to any of the platforms, the flight time decreases because more energy is required by the motors. Aside from the fixed-wing eBee, the flight times of these platforms range from 15 to 30 min. The flight times are reported from manufacturer-conducted flight endurance testing. The exact parameters, other than time and weight, of the flight testing are not necessarily reported. The unknown parameters will result in some variance with respect to flight times. These parameters may include battery level at flight termination, ambient or battery temperature, flight pathing, and wind. For this reason, users can expect variation from manufacturer-reported values when using a platform. As users gain experience, they become competent at estimating flight times depending on environmental conditions and flight aggressiveness (velocity and acceleration).

Fig. 4 contains a compilation of the multirotor platforms summarized in Table 1. The Matrice 600 and Matrice 100 UAVs have

Table 1. Specifications of popular commercial UAV platforms

Index	Platform	Type	Takeoff weight (g)	Max speed (m/s)	Max flight time (min)	Diameter or wingspan (mm)	Integrated camera?	Open source?	Customizable payload?
1	DJI Inspire 2	Quadrotor	3,440	18	15	559	Yes	No	No
2	DJI Inspire 1	Quadrotor	3,060	22	18	559	Yes	No	No
3	DJI Mavic Pro	Quadrotor	743	18	27	335	Yes	No	No
4	DJI Phantom 4 Pro	Quadrotor	1,388	20	30	350	Yes	No	No
5	DJI Phantom 4	Quadrotor	1,380	20	28	350	Yes	No	No
6	DJI Phantom 3 Pro	Quadrotor	1,280	16	25	350	Yes	No	No
7	DJI Phantom 2 Vision+	Quadrotor	1,242	15	25	350	Yes	No	No
8	DJI Phantom 2	Quadrotor	1,242	15	25	350	No	No	No
9	Spreading Wings S1000	Octorotor	9,500	16	15	1,045	No	No	Yes
10	Spreading Wings S900	Hexarotor	6,800	16	18	900	No	No	Yes
11	DJI Matrice 100	Quadrotor	2,855	22	17	650	No	Yes	Yes
12	DJI Matrice 600	Hexarotor	15,100	18	16	1,833	No	No	Yes
13	3DR Solo	Quadrotor	1,990	25	25	460	No	Yes	No
14	3DR Iris	Quadrotor	1,282	23	20	550	No	Yes	No
15	Yuneec Typhoon 4K	Quadrotor	1,700	8	25	420	Yes	No	No
16	Yuneec Typhoon H	Hexarotor	1,950	19	25	520	Yes	No	No
17	SenseFly Albris	Quadrotor	1,800	12	22	800	Yes	No	No
N/A	SenseFly eBee	Fixed wing	690	25	50	960	Yes	No	No

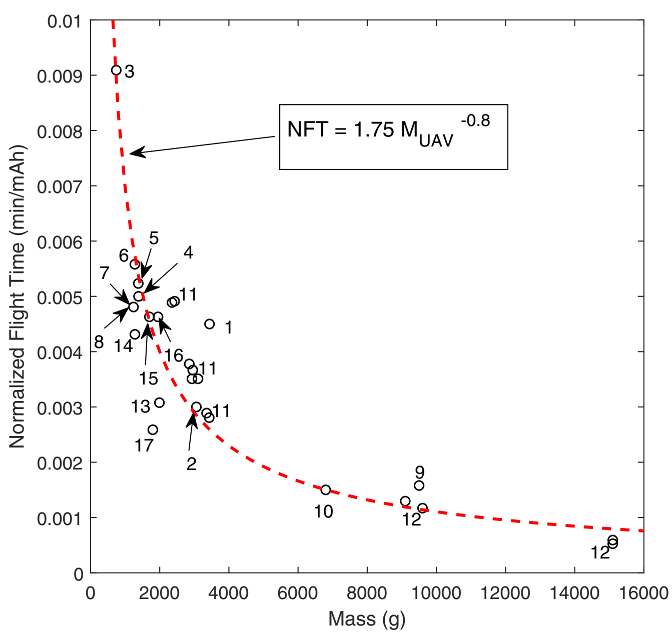

Fig. 4. Empirical relationship between total weight, flight time, and battery capacity derived from 26 commercially available UAV configurations. Labels correspond to index values in Table 1.

multiple points in Fig. 4 because they have more extensive flight endurance testing including different battery and payload combinations. Flight time is normalized by total battery capacity (in terms of milliampere hour) and shown to be a function of the UAV total mass. As is evident from the plot, the normalized flight time (NFT) is inversely proportional to the total UAV mass (M_{UAV}). A regression analysis is performed and it is found that

$$\mathrm{NFT} = 1.75 M_{\mathrm{UAV}}^{-0.8} \quad (R^2 = 0.87) \tag{1}$$

This relationship is important because it captures the physics of UAV flight and the energy needed to fly UAVs of a specific weight for a period of time. More importantly, it provides UAV operators a means of accurately predicting how long an UAV would operate if the payload is altered. As seen in subsequent sections, researchers often modify UAVs to carry sensing payloads of varying size and weight. The flight time-mass (NFT–M_{UAV}) curve provides such researchers a means of estimating their flight times independent of their UAV platform. Additionally, the curve can be used to estimate the impact of changing battery and payload configurations on a given platform. Researchers who change their UAV's payload often or have an application in which the UAV's total mass varies during flight may find developing a platform-specific curve similar to Fig. 4 useful (e.g., Greenwood et al. 2018). In the authors' experience using the DJI Matrice 600 Pro hexarotor UAV with a battery capacity of 27,000 mAh, a takeoff weight of 9.5 kg results in an approximate flight time while hovering in 0–1.6 km/h (0–5 mi/h) wind of 35 min, and a takeoff weight of 16.8 kg results in an approximate flight time of 16 min while hovering in 0–1.6 km/h (0–5 mi/h) wind. Eq. (1) predicts 31 and 19 min for these payload conditions, respectively.

As can be noted from Table 1, the most popular UAV platforms have integrated cameras or are intended to carry a camera as the primary sensing payload. This is a reflection of the fact that most UAV-based applications have been based on collecting imagery, as discussed subsequently in this paper. When selecting an UAV platform, it is important to understand what the UAV will need to do and to select a platform that meets those needs. This would be more efficient than preselecting a platform and then attempting to make significant alterations that allow the UAV to meet the needs of the application. Table 1 may provide guidance for novice UAV users looking to select an appropriate platform for their application. After exploring off-the-shelf products, researchers may be interested in constructing their own specialized platforms. In general, it is recommended that novice UAV users gain experience using lower cost quadrotor platforms before expanding into larger, heavy-lift multirotors and open-source frameworks. Open-source software frameworks allow for the integration of external sensors into the UAS, the implementation of user-defined control algorithms, and operational parameters for specific applications. The knowledge base for camera-equipped multirotors is vast and should allow new users to advance quickly assuming sufficient experience is gained and safety procedures are implemented. Newer users should be aware of and ensure safety components are contained in the UAS. This includes flight termination, return to home, virtual tethers, and geofencing. These components are critical in cases of lost/poor communication during flight. Communication range is typically not a critical consideration because most ranges for UAV to remote control extend far beyond what is needed for line-of-sight flying (reported to be several thousand meters). Communications disruption caused by physical obstruction or signal interference are much greater concerns. It is recommended that novice users also avoid GPS-denied environments (e.g., tunnels and mountainous regions) until experience is gained and greater understanding of other navigation methods, such as vision-based localization, is developed. Other factors, such as noise generation, may not be reported by the manufacturer and are not typically a major consideration for most researchers outside of ecological and human-interactive applications. Weather conditions must be monitored including precipitation, temperature, and wind. Few commercial platforms are capable of handling precipitation, or even high-moisture, environments. Most multirotor platforms are highly susceptible to precipitation, particularly due to overexposure of motors which is necessary for heat dissipation. Low temperatures have a significant impact on battery performance and some platforms may use battery warming systems to maintain a minimum battery temperature.

UAV-Deployed Sensors

The use of UAV-mounted red, green, and blue (RGB) cameras is the dominant configuration in the current literature. This is evident in earlier reviews that focus on UAV-based imaging applications in civil engineering (Ezequiel et al. 2014; Chan et al. 2015; Ham et al. 2016; Jordan et al. 2018). However, many other types of sensors on UAVs can play a role in civil engineering for multiscale data collection, remote sensing, and even sample collection. It should also be noted that non-RGB and multimodal imaging is becoming more common on UAVs including hyperspectral imaging (Crocker et al. 2012; Lin et al. 2013) and thermal imaging (Berni et al. 2009; Nishar et al. 2016). This section provides examples of nonimaging sensors used in applications relevant to infrastructure systems; the most popular of these sensors is LiDAR (Nagai et al. 2009; Lin et al. 2011). The most popular approach to using LiDAR is to map the UAV's surrounding environment. Kaul et al. (2016) developed a 3D mapping system using a rotating two-dimensional (2D) LiDAR scanner capable of 3D mapping in a GPS-denied environment. LiDAR is mentioned several times in the section "UAV Applications in Civil Infrastructure Systems" as both an airborne sensor and as a terrestrial sensor used in UAV data synthesis. The differences between results produced by LiDAR and structure from motion (SfM) (Snavely et al. 2008; Westoby et al. 2012) have been thoroughly compared. In this section, a discussion of some of the numerous comparisons between LiDAR and image-derived point clouds is provided.

Sensing Payloads

Despite the prevalence of RGB cameras and, to a lesser extent, LiDAR, other sensors have been implemented in a variety of fields. Many of the nonimaging sensors and their associated applications are summarized in Table 2. The list in Table 2 is not exhaustive and includes study areas outside of civil engineering to demonstrate the breadth of sensors being used on UAVs. Some of the sensor types, such as hyperspectral and thermal imaging and synthetic aperture radar (SAR) are fundamentally similar to the RGB imaging and LiDAR sensing techniques. Brooks et al. (2014) and Nishar et al. (2016) provide examples of thermal imaging using infrared (IR) sensors from an UAV for bridge deck inspection and geothermal field mapping, respectively. Secondary imaging techniques can be coupled with traditional RGB camera outputs such as orthophotos and 3D point clouds. Combining nontraditional imaging with RGB images produces multimodal images which are valuable for data synthesis when analyzing infrastructure system components.

Biological sensors are used in civil and environmental engineering fields to identify specific airborne contaminants or pathogens. They are categorically similar to gas and radiation detection because they require contact between the sensor and the target. Unsurprisingly, all of the listed sensor types in Table 2 include a spatial data collection component. This is expected due to spatial mobility being a strength of UAV platforms. Magnetometers are the only sensor listed in Table 2 capable of probing beneath the ground surface. This is a frontier area for UAVs that has not been investigated extensively yet but has significant relevance to geotechnical infrastructure systems such as pipelines, levees, earth dams, landfills, and subsurface hazard detection.

All sensors mentioned in Table 2, as well as cameras and LiDAR, require some degree of confidence in the UAV's positioning. The absolute accuracy needed for the UAV positioning will depend heavily on sensor type and the specific application. The positioning provided by standard GPS units is generally suitable for collecting relatively coarse geospatial data. RTK positioning systems have started to be developed for small UAVs in recent years and can provide positioning accuracy as low as 1 cm. However, achieving such accuracy is only attainable if position is held for some time (minutes). For example, Turner et al. (2016) found that manually surveyed control points were no longer necessary for coastal surveys of beaches when using UAV-mounted RTK-GPS systems. Tziavou et al. (2018) recommended using a minimum

Table 2. UAV-based sensors and corresponding applications

Sensor type	Applications	References
Gas detection	Volcanology, environmental monitoring, climatology	Rossi and Brunelli (2016); Malaver et al., (2015); Rosser et al. (2015); and McGonigle et al. (2008)
LiDAR	Civil engineering, glaciology, forestry, precision agriculture, mapping	Eschmann and Wundsam (2017); Hirose et al. (2015); Yang and Chen (2015); Zarco-Tejada et al. (2014); Lin et al. (2013); Crocker et al. (2012); Wallace et al. (2012); Lin et al. (2011); Nagai et al. (2009)
Biosensor	Agriculture, environmental monitoring	Lu et al. (2015); and Techy et al. (2010)
Magnetometer	Geophysics/geology/geotechnical engineering	Wood et al. (2016); and Forrester et al. (2014)
SAR	Glaciology, mapping	Leuschen et al. (2014); Frey et al. (2009); and Xing et al. (2009)
Temperature	Glaciology	Crocker et al. (2012)
Thermal imaging	Precision agriculture, geology/geotechnical engineering	Eschmann and Wundsam (2017); Nishar et al. (2016); Calderón et al. (2013); and Berni et al. (2009)
Multispectral imaging	Precision agriculture	Candiago et al. (2015) and Berni et al. (2009)
Hyperspectral imaging	Precision agriculture, glaciology	Calderón et al. (2013) and Crocker et al. (2012)

Note: SAR = synthetic aperture radar.

of one point surveyed on the ground surface for control of the vertical positioning component. The innovation of UAV-based RTK-GPS has improved the already robust aerial surveying methods used with UAVs. Removing the need for broadly distributed ground survey points for image-based surveying makes the methods even more competitive. Advanced RTK positioning methods, such as those using network-based architectures, have great potential to benefit data collection for all integrated sensors and should be pursued in research.

Comparison of LiDAR and Camera-Based Surveying

The dominant photogrammetry technique adopted to derive 3D point clouds from UAV imagery is SfM. SfM utilizes sequences of overlapping images to extract features and derive 3D information. Camera positions and orientations are indirectly derived from the imagery using a bundle adjustment algorithm. Models are then scaled and georeferenced using physical ground control points (GCP) with known locations. The density and location of GCPs used to scale a model have a significant impact on the mean error and distribution of error within the model (Manousakis et al. 2016; Agüera-Vega et al. 2017). Adaptations of traditional SfM have also been introduced, such as methods specifically tuned for infrastructure assessment. Both LiDAR and optical cameras can be used to generate 3D point clouds. In the section "UAV Applications in Civil Infrastructure Systems," many instances of aerial surveying for SfM are outlined. LiDAR point clouds have the advantage that they are not as significantly affected as optical cameras by semipenetrable obstacles such as vegetation or water. LiDAR scanning relies upon knowing the position and orientation of the scanner. This can be difficult to manage when mounted on an UAV. Comparatively, camera positions can be determined from consecutive images in photogrammetric techniques. LiDAR scanners are also much heavier than typical cameras. However, recent interest in UAV-mounted LiDAR has resulted in concerted efforts to make LiDAR scanners smaller and lighter (and cheaper). For example, the Velodyne LiDAR Puck has a mass less than 1 kg and is about 100 mm in diameter with a laser pulse range of 100 m.

Hugenholtz et al. (2013) used a small, fixed-wing UAV to map and identify surface geomorphologic features. UAV imagery was used to develop a digital terrain model (DTM). The authors found that the error of the image-based DTM, relative to a GPS survey, was comparable to a LiDAR DTM of the same site. Siebert and Teizer (2014) used an UAV with mounted RGB camera as a surveying tool for construction projects and compared UAV-based photogrammetry with conventional surveying methods as ground truth. The possible sources of error in UAV surveying are also discussed in depth in Siebert and Teizer (2014). Fig. 5 illustrates a comparison of UAV-based photogrammetry to other surveying methods in terms of total coverage area and survey error; arrows have been added to demonstrate existing, and potentially future, expansion of the UAV photogrammetry region initiated by advancements in camera hardware, imaging methodologies, and UAV control. Hugenholtz et al. (2014) showed that centimeter-scale DTMs developed from UAV-based photogrammetry are a competitive alternative to LiDAR scans. Additional discussion on the post-processing implications of UAV-collected LiDAR scans is presented in the following section.

System Integration and Data Processing Challenges

UAS contain processing power which has the potential to transform them into advanced computational platforms for real-time decision making for management of complex infrastructure systems.

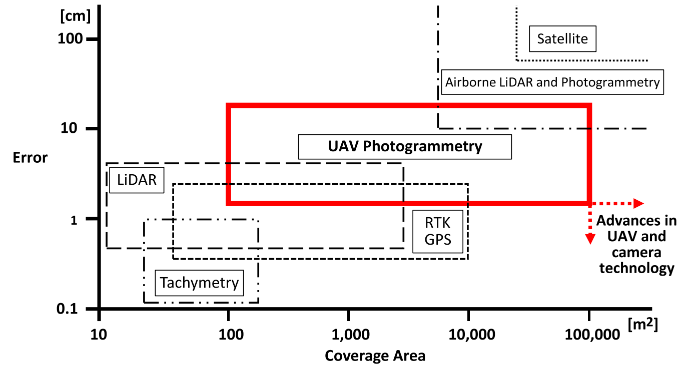

Fig. 5. UAV application to surveying tasks. (Adapted from Siebert and Teizer 2014.)

For example, UAVs have been integrated in many wildfire monitoring and firefighting schemes to protect towns and communities (Yuan et al. 2015). Barrado et al. (2010) described the integration of UAS in a multilayered network including firefighter, tethered communication relays, and surveillance UAVs. Murphy et al. (2015) explored the integration of UAVs with immediate post-disaster reconnaissance and search-and-rescue efforts. Similar efforts are yet to be made fully incorporating UAVs into civil infrastructure systems; however, the greatest strides in this direction have been made in the construction management community (Ham et al. 2016).

Wireless Sensor Networks

It has been theorized and demonstrated that the spatial and temporal flexibility of wireless sensors coupled with their computational capabilities are ideal attributes for utilizing networks of wireless sensors with UAVs (Mascareñas et al. 2009; Maza et al. 2011; Jawhar et al. 2014; Zekkos et al. 2014; Malaver et al. 2015; Greenwood et al. 2016b; Zhou et al. 2016). Wireless sensors are a critical component of state-of-the-art structural health and infrastructure monitoring. Mascareñas et al. (2009) proposed a mobile host wireless sensor network paradigm. The proposed paradigm utilizes wireless sensor nodes powered and interrogated by a mobile host, such as an UAV. This methodology would improve data collection efficiency and make for a more cost-effective wireless sensor network integration for infrastructure monitoring. Data collection and sensor node interrogation by UAV makes using widely distributed sensor networks more attractive. Networks distributed over large spatial areas can be very expensive and time consuming to maintain. Specifically, deploying WSN over large areas necessitates significant infrastructure such as power sources and long-range communication networks. Recently, there have been significant efforts made to improve incorporating UAVs with WSN to both provide power and also to collect data (Fadlullah et al. 2016). Cobano et al. (2010) developed a path-planning method for optimal data collection from stationary wireless sensor nodes. Flight path waypoints were selected on the basis of a heterogeneous distribution of sensor nodes while considering safety and required proximity for communication with the sensor nodes. Dong et al. (2014) discussed some challenges of collecting sensor data with UAVs, such as coordinating platform velocity with sensor network density. An algorithm for mobile agents to aggregate sensor data over specific regions before transmitting packaged data to the UAV was also proposed. Ho et al. (2015) discussed the selection of wireless sensor network communication topology to optimize the efficiency of communicating data.

When recovering data from distributed networks, efficiency is critical due to the presently limited endurance of most small UAVs. Optimizing flight path for communication with ground-based sensors is also a concern for fixed-wing platforms. A fixed-wing platform will have efficient flight for covering large distances to communicate with a distributed sensor network or along a pipeline. But, a fixed-wing platform cannot hold position, so communication must occur while the UAV is flying past the sensors. The efficiency of wireless networks can also be improved with UAVs. Villas et al. (2015) proposed using the GPS receiver onboard to solve localization and time synchronization among sensor nodes. This would eliminate the need for individual nodes to contain their own GPS receiver. Kim and Choi (2015) developed an ad hoc 3D localization scheme for UAVs in GPS-denied environments by leveraging ground-based and airborne sensor nodes. Acquiring UAV position from ground-based sensor nodes presents some difficulties when expanded to 3D localization. Airborne sensor nodes, namely other UAVs, can be used to determine the position and relative distances with other communicating UAVs.

The deployment of wireless sensors by UAVs has also been explored on a limited basis. Maza et al. (2011) used multiple autonomous helicopter UAVs to deploy wireless sensor nodes and IR cameras for a firefighting proof-of-concept test. Wireless nodes contained sensors for temperature, humidity, carbon monoxide, and smoke. Sensor nodes were attached to firefighters at the site and additional nodes were distributed by UAV to monitor the movement of fire to sensitive locations in a building. UAV was also used to deploy optical and IR cameras on the top of a building providing real-time information on fire propagation, firefighters, and victims. Zhou et al. (2016) used an UAV to physically distribute and mount accelerometers on a simple beam structure using a robotic arm mounted to the UAV. The UAV placed wireless sensors on the structure and communicated with them to record data while introducing an impulse for modal analyses. The major limitation to sensor deployment by UAVs is the limited payload capacity of small UAVs and the reduced flight endurance caused by sensor payloads (e.g., Fig. 4). Distribution of many sensor nodes by a single UAV is a task with significant logistical challenges. A more efficient approach may be to have a series of small UAVs, or a swarm, individually transport and place sensor nodes, especially for short-term placement.

UAV-Specific Data Reduction

Remote sensing methods that have been incorporated on UAVs often require additional (and extensive) data processing (Frey et al. 2009; Harwin and Lucieer 2012; Hirose et al. 2015). Examples of this include the data associated with UAV-based SAR (Frey et al. 2009), LiDAR (Brooks et al. 2014; Hirose et al 2015), magnetic surveys (Wood et al. 2016), and high-resolution imaging (Harwin and Lucieer 2012). The uncertainty of UAV position and pose propagates as uncertainty in the collected data but can often be eliminated with correcting algorithms. The reliability of UAV-based LiDAR data is highly dependent on confidence in UAV pose and position estimations. In response to this, recent attempts have been made to improve the reliability of LiDAR data collected on an UAV through signal processing or synthesizing with other data sources (e.g., Lin et al. 2013). One approach, employed by Droeschel et al. (2016), is to connect many sensor types on a single platform. Droeschel et al. (2016) combined stereo cameras, ultrasonic sensors, and LiDAR to map obstacles for UAV navigation. Hirose et al. (2015) demonstrated UAV-based LiDAR monitoring of structures in a GPS-denied environment but noted the issue of pose uncertainty in LiDAR point cloud results. Understanding the pose and motion of the UAV is imperative for LiDAR measurements and becomes most difficult in GPS-denied environments. Hirose et al. (2015) implemented an iterative closest point algorithm to correct resulting distortions in the LiDAR point cloud. UAV localization was improved by feeding inertial measurement unit (IMU) and camera data into a Kalman filter. Brooks et al. (2014) used UAV-mounted LiDAR to develop 3D models of a highway bridge. A 3D simultaneous localization and mapping (SLAM) algorithm was used to improve the quality of the LiDAR point cloud. Fig. 6 shows the 3D LiDAR results before and after scan-matching alignment. Sensor payload orientation and positioning can be measured using onboard IMU sensors, but may contain debilitating errors and must be addressed through post-processing of IMU data (Brooks et al. 2014; Hirose et al. 2015; Gautum et al. 2017; Klingbeil et al. 2017). Some recently developed UAV platforms utilize multiple sets of IMU and GPS receivers to improve localization redundancy. As previously mentioned, the uncertainty of UAV position has become a less-critical concern in GPS-enabled environments and when utilizing some imaging methods such as SfM. Processing methods specifically for data collected in GPS-denied environments, such as in buildings or in remote valleys, must still be pursued. Vision-based methods for localization are being investigated extensively, partly to address this issue.

UAV-based photogrammetric techniques such as SfM and multiview stereo (MVS) quickly became popular because they have become well-established and validated methods; they are also resistant to some of the problems associated with remote sensing by UAV such as pose estimation. This is because of the robustness

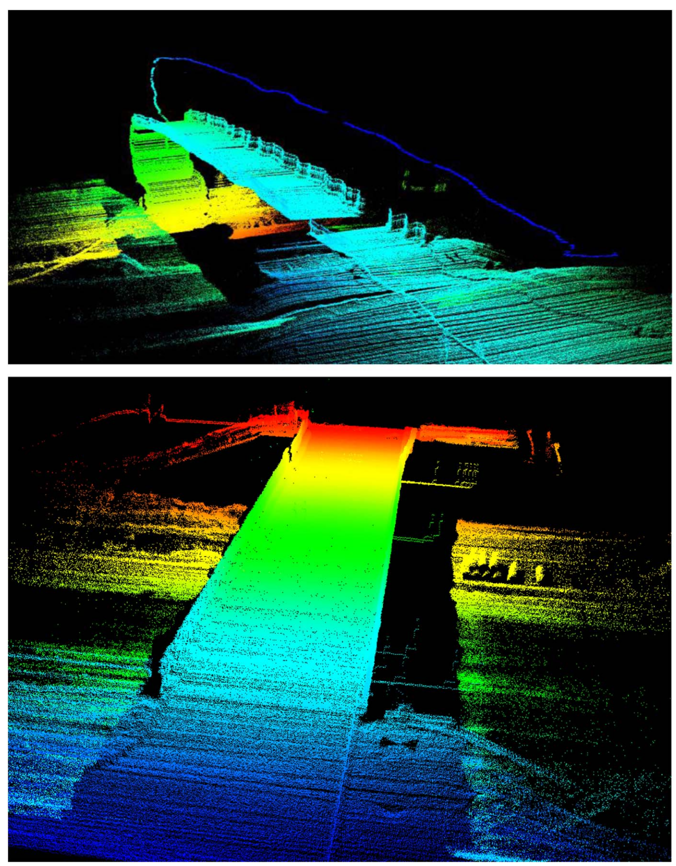

Fig. 6. LiDAR scan of bridge deck: (a) before and (b) after altitude estimate and scan-matching alignment. (Adapted from Brooks et al. 2014.)

of camera pose extraction from a series of images in photogrammetric methods and the reliability of feature detection algorithms developed for computer vision and image processing such as scale-invariant feature transform (SIFT) (Lowe 1999, 2004). New image-processing methods have been developed or expanded based on the collection of UAV-based images. Jahanshahi et al. (2017) approached the issue of positional inaccuracies and outliers in SfM, developing an algorithm to improve 3D reconstruction when misassociated features exist in the SfM data. The algorithm was used following standard outlier rejection methods within the bundle adjustment process.

Adaptations of traditional SfM have also been introduced, such as methods specifically for infrastructure assessment, based on the same algorithm structure. For example, Khaloo and Lattanzi (2017) presented a dense SfM approach used to resolve small-scale details needed for infrastructure inspection. However, other photogrammetry and computer vision techniques can be used, including those dependent on directly measuring camera position and orientation. Direct measurement of camera position and orientation can be made using onboard inertial sensors and GPS (Cucci et al. 2017; Klingbeil et al. 2017). Irrespective of the method used to derive them, 3D topological models provide engineers with a quantitative measurement of the topologies corresponding to ground and structural surfaces. Carpin et al. (2013) developed a variable-resolution object detection method. This object search method utilizes the ability of UAVs to rapidly adjust imaging resolution by changing vehicle altitude. Vetrivel et al. (2015) developed an image segmentation methodology for UAVs. Images are collected by an UAV and used to produce a 3D point cloud. The point cloud is segmented and used to similarly segment the original UAV-collected images.

Novel methodologies in infrastructure system monitoring and inspection can be expected to be extended to UAV platforms in the near future, such as the crack detection and quantification method developed by Jahanshahi et al. (2013), 3D crack detection developed by Torok et al. (2014), crack change detection method by Adhikari et al. (2016), 3D city modeling by Cornelis et al. (2008), and digital image correlation (Take 2015). The potential extension of these imaging techniques is enabled by increasing onboard computational capacity and its use for real-time processing.

UAV Applications in Civil Infrastructure Systems

Over the last decade, UAVs and other robotic systems have shown tremendous promise for use in a wide variety of applications in the realm of civil infrastructure systems (Lattanzi and Miller 2017). Fundamentally, UAVs are revolutionizing the field by providing previously unattainable data collection capabilities that surpass existing methods in terms of ease, accuracy, and cost. Using FAA UAS exemption applications as a metric, Fig. 7 shows the broad number of applications submitted through January 2016 that identify an infrastructure-related use (AUVSI 2016). The attraction of integrating UAVs in many civil infrastructure applications is primarily based on accelerating accessibility to remote and dangerous sites, sensor mobility, and overall speed of data collection. Any application that could utilize a highly mobile data collection or communication platform could conceivably incorporate UAVs as a primary data collection component. In particular, UAVs have begun to emerge as an essential data collection tool for applications involving natural hazards (e.g., earthquakes and hurricanes) in which site accessibility can be challenging post-event and the need to collect highly perishable data is urgent. In such applications, UAV-based photogrammetry provides advantages over other remote sensing platforms such as satellites and people on the ground (Colomina and Molina 2014). Satellites are limited by return time, cloud coverage, image resolution, and collection of imagery primarily in plan view. UAVs can be deployed on demand, and flight parameters can be adjusted to acquire the desired image resolution and perspective. Human teams on the ground (walking or using ground-based vehicles) can be challenged by treacherous terrain, physical obstacles, or dangerous site conditions. As a result of these challenges, UAVs also offer an economic advantage including reduction of costs associated with personnel, travel, and site logistics. The role of UAVs can also go well beyond photogrammetry by offering the possibility to carry other sensor types for data collection, a role in processing data, and interacting with users on the ground. The top application areas in civil infrastructure in which UAVs have had transformative impact on the state of practice are infrastructure system component monitoring, construction safety and progress monitoring, geotechnical engineering, and post-disaster reconnaissance. These application areas are described in this section to provide the reader with insight into how UAVs may be used on-site with clear benefit to the application. Lessons learned and the gaps in knowledge identified by this paper's authors in these domains are further discussed in the conclusions of the review. It is important to identify other reviews related to the use of UAVs because they may pertain to civil infrastructure. Ezequiel et al. (2014) reviewed applications in post-disaster assessment, environmental management, and infrastructure development in which UAV-based remote sensing is used within

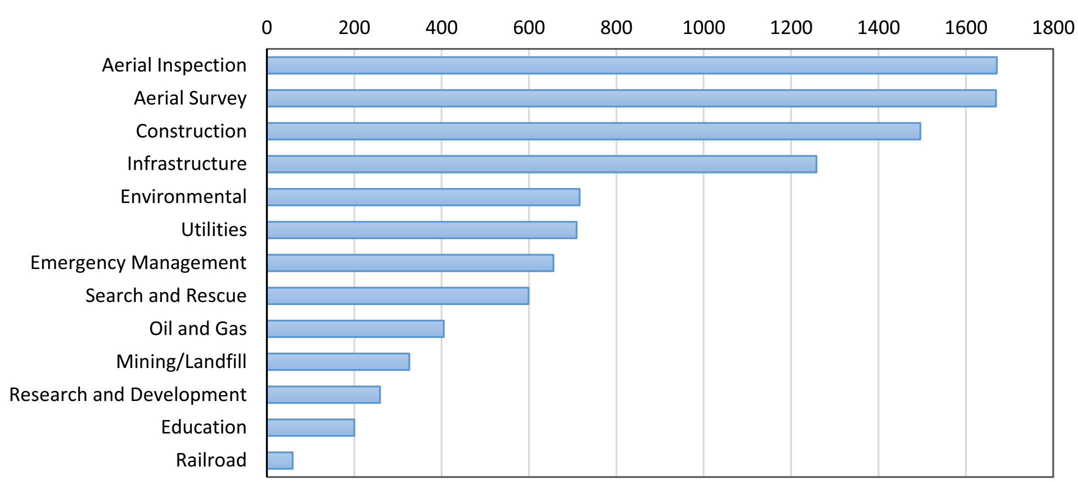

Fig. 7. Number of civil engineering–related applications cited in FAA UAS exemption applications. (Data from AUVSI 2016.)

data-sharing networks. A broad overview of application areas in civil engineering was reviewed by Liu et al. (2014) with a strong focus on control. Colomina and Molina (2014) provided an in-depth review of UAV-based photogrammetry with RGB cameras. The review also provides insight into remote sensing in which UAVs have been utilized and includes details of other camera types for UAV-based remote sensing (e.g., multispectral). A targeted review of UAVs as bridge inspection was presented by Chan et al. (2015). Vision-based efforts for monitoring infrastructure were reviewed by Ham et al. (2016) from a construction perspective. This review provides a useful synthesis of contributions from the robotics and computer vision communities. Lattanzi and Miller (2017) presented a thorough overview of robotic platforms used to inspect infrastructure components. This review details inspection robots of several different mobility types including aerial, underwater, ground-based, and climbing robots. Jordan et al. (2018) provided a contextual review of UAV-based inspection of power facilities and structures. The review discusses the critical technologies addressing current implementation challenges.

Monitoring of Infrastructure System Components

In this section, key cases of UAVs being used for infrastructure monitoring are discussed. The discussion begins with monitoring linear structures such as pipelines, then bridge inspection and monitoring, and finish with UAVs applied to monitoring traffic conditions in transportation systems. For each of these topics the discussion is presented chronologically. Clearly, there is a large number of infrastructure system components that can be, and have been, monitored by an UAV. The topics in this section have been selected by the authors of this paper due to the prominence of the topics in the UAV literature. The use of UAVs to monitor other infrastructure components and features such as road surfaces, power lines, concrete dams and communication towers among many others should not be discounted.

As previously mentioned, UAVs can be useful, low-cost tools for visual inspection and monitoring of infrastructure systems at many scales (Lattanzi and Miller 2017). In the US, "infrastructure" was listed as an application for about 40% of FAA exemptions as of January 2016 (AUVSI 2016). Rathinam et al. (2008) used an UAV with a predetermined flight path to inspect linear structures, such as pipelines. Rathinam et al. (2008) also proposed a real-time, vision-based detection algorithm for linear structures. However, frame-by-frame operations on the video feed were found to be too computationally intensive. UAVs have onboard computational capabilities which has greatly improved in recent years, but the computationally intensive nature of real-time image processing is a consistent point of emphasis in the literature, especially as camera technology (i.e., increasing resolution and multimodal imaging) improves. Pipelines represent an infrastructure component with significant consequences of failure. Monitoring of pipelines over a large spatial range is therefore critical to their performance. Due to the significant distances covered by similar types of infrastructure, such as railroads, levees, powerlines, and pipelines, rapid data collection over large distances is desirable. For example, Gao et al. (2011) investigated the use of UAVs for data collection of geologic hazards threatening pipelines. Jawhar et al. (2014) proposed a strategy for collecting data via UAV from sensor arrays distributed on pipelines. The characteristic nature of monitoring a linear structure such as a pipeline can be applied across the other examples mentioned previously. Monitoring over large, rural areas allows infrastructure in these places to receive newfound attention and improves the response rate to performance changes. The risk associated with UAV failure is also lower relative to urban environments. However, depending on consequences, monitoring over such expanses can be too costly (Jawhar et al. 2014). The relative cost of using an UAV over large distances is much lower for fixed-wing platforms. If functions that require multirotor platforms must be performed, the monitoring effort could quickly become unsustainable. This is one area in which the authors of this paper believe VTOL platforms will have a profound impact as their usage expands.

UAV-based remote sensing for critical infrastructure is a possible method to aid visual inspection, or in some cases completely replace inspectors in the field. In fact, bridge inspection is the most widely approached topic for UAV integration in infrastructure monitoring. Ellenberg et al. (2014a) used an UAV for visual inspection of bridges for deformations and cracking. The algorithms proposed by Ellenberg et al. (2014a) suggest placement of markers tracked in 3D by photogrammetry or 3D SLAM. Similarly, Ellenberg et al. (2014b) used an UAV to collect imagery of cracked masonry. Several crack detection algorithms were used on the imagery including edge detection, percolation approach, fractal method, and tensor voting. Lattanzi and Miller (2015) used an UAV to collect images of bridge structural elements and generate 3D models. The UAV-based imaging is demonstrated as a low-cost, computationally efficient way to repeatedly model structures and compare with previous models. Brooks et al. (2014) used UAVs for bridge inspections and expanded the role of UAVs beyond using traditional imaging by including thermal imaging as a component of bridge inspection. Gillins et al. (2016) also demonstrated bridge inspection with a low-cost UAV. Emphasis was placed in leveraging the mobility of the UAV to acquire images at many viewing angles of critical details such as fasteners, joints, and evidence of material deterioration. Implementations of bridge inspection are numerous but have some general limitations. There are few recommendations made for practical implementations which combine visual inspection with sensor-based health monitoring. Additionally, it is still challenging to acquire high-resolution images of the most obscure or difficult-to-reach fasteners. Future work into obstacle avoidance and localization within the spatial challenges of bridges will help alleviate the limitations. Zhou et al. (2016) demonstrated the deployment of mobile wireless sensors onto a structure by an UAV, as discussed previously. The implementation of UAVs for the deployment and redistribution of wireless sensor nodes has the potential to enhance the distributed data collection required for infrastructure monitoring as well as improve the safety and efficiency of distributing sensor nodes. Eschmann and Wundsam (2017) developed a multi-sensor UAV bridge inspection platform to carry three sensors: long-wavelength IR, optical camera, and LiDAR. Each sensor performed different tasks which were then fused into a complete 3D visualization. Surfaces and deformation were recorded using the LiDAR, images from the optical camera were used to overlay model textures and monitor cracks, and the IR camera was used to detect moisture around cracks. Hackl et al. (2018) used UAV-based photogrammetry to develop 3D meshes of a 24-m span, reinforced concrete bridge and surrounding terrain in Switzerland. The meshes were integrated with hydrodynamic models to simulate complex flow scenarios and perform risk assessments. Khaloo et al. (2018) used an UAV to develop a 3D model of a timber truss footbridge for detecting defects and inspecting connections. The model was developed from over 2,000 photos acquired from 22 different flight paths around the 85-m span bridge. Three-dimensional imaging is extremely popular in structural monitoring as well as many other fields. However, most studies utilizing robust 3D imaging do not demonstrate implementation of 3D outputs in further analysis. Hackl et al. (2018) demonstrate how detailed imagery of a bridge can be transferred to hydrodynamic models, thus promoting collaboration and cross-field use of data.

Traffic surveillance and monitoring was explored as one of the first applications for UAVs in civil engineering (Srinivasan et al. 2004; Coifman et al. 2006). Traffic modeling based on UAV-collected data was demonstrated by Coifman et al. (2006). Recent efforts have been made to use UAVs for streamlining roadway condition assessments. Several state DOTs have already begun to implement UAVs in recent years (Barfuss et al. 2012; Brooks et al. 2014; Irizarry and Johnson 2014). Zhang and Elaksher (2012) used UAV-collected imagery to produce 3D models of distressed unpaved roads. A 3D model with absolute resolution less than 1 cm was used to detect potholes and ruts within the roads. Dobson et al. (2013) developed a system for detecting damage on unpaved roads. A helicopter UAV was used to collect imagery of unpaved roads and produce 3D point clouds. Potholes are detected in the point clouds using Canny edge detection and Hough circle transform algorithms. Brooks et al. (2014) explored possible applications for UAVs in transportation engineering and found UAVs to be cost-effective tools for monitoring traffic and inspecting road assets. Additional applications such as crash scene reconstruction, roadside slope stability assessments, and optimizing platforms for sharing UAV data sets are offered as needed research concentrations by the authors. Data collection on the performance of transportation systems within civil infrastructure is often sparse and can ignore specific details. For example, conventional traffic counting may ignore vehicle type and speed, vision-based data collected by UAV can provide greater detail when monitoring traffic patterns. This level of detail can also be acquired using fixed cameras, but an UAV can be mobilized to many locations without requiring equipment installation at locations where constant, or long-term, surveillance is unnecessary. The desire of state governments to develop new methodologies based on data collection with UAVs may help facilitate the development of positive regulatory environments.

Construction Safety and Progress Monitoring

Using UAVs in construction management is developing into a staple of the construction industry. Construction was the fifth most cited application among FAA UAS exemptions as of January 20, 2016, appearing in nearly half of the exemptions (AUVSI 2016). In this section, key examples of UAVs being used for construction management are discussed. The discussion begins with excavations, then considers progress monitoring for construction projects, and concludes with UAV-based safety concerns and interaction with construction personnel. For each of these topics the presentation is chronological.

Documenting construction progress in urban excavations is critical due to the damage construction-induced deformations can cause to nearby infrastructure (Hashash et al. 2015b). Development of 3D models at construction sites over time to document progress has been the most common application of UAVs in construction management. Lin et al. (2015) proposed a model-driven, automated methodology for construction progress monitoring. The monitoring method was intended to replace manual image collection with efficient, more complete documentation collected via automated UAV. The proposed methodology utilizes building information modeling (BIM) to drive the autonomous data collection. Recent research efforts have also included more than updating images, with a focus on resource tracking at construction sites (Teizer 2015). Lin and Golparvar-Fard (2016) developed a web-based system to track construction workflows utilizing BIM. Irizarry and Costa (2016) also demonstrated additional uses for UAVs on construction sites beyond documenting progress; images collected by the UAV at construction sites in the United States and Brazil were used to identify and track specific management tasks and became part of an asset database. The work demonstrated by the construction management community has pioneered the augmentation of established workflows with UAS. Efforts have been made to use UAV platforms to go beyond data collection and approach system integration.

The development of underground space in cities emphasizes the need for monitoring techniques for subsurface excavations (Fleming et al. 2016). Fleming et al. (2016) used a low-cost UAV to monitor excavation bracing in an urban excavation site. UAV imagery was used to generate 3D models over time. One of the top challenges for using UAVs for excavation inspection and monitoring is that they often need to perform in GPS-denied environments. In particular, subsurface construction such as excavations and tunneling have a need for nearly continuous monitoring of small displacements. Operating UAVs in GPS-denied environments with poor localization will make the measurement of small displacements problematic.

UAVs have also been explored as safety inspection tools on construction sites. Innovative technologies such as UAVs, wireless sensor networks, and information technology are expected to be essential for construction and safety management (Irizarry et al. 2012; Zhang et al. 2015). Irizarry et al. (2012) explored the use of low-cost UAVs as tools for safety managers on construction sites. The UAV provided the safety manager with rapid access to images anywhere on the site. Irizarry et al. (2012) found that a camera-equipped UAV with a large visual interface was just as effective for the safety manager as making direct observations in plain view. They also recommended specific features that should be required of construction safety UAVs such as autonomous flight, voice recognition, and a user-interface useful for collaboration. It should be noted that incorporating UAVs in active construction sites introduces additional safety concerns such as personnel distraction and increased collision risk with equipment or personnel (Irizarry et al. 2012). Training of construction site personnel is necessary for safe UAV integration (Irizarry and Costa 2016). These factors are all critical considerations for integrating UAVs into infrastructure construction practices. This notion is highlighted by the envisioned next-generation construction site presented by Ham et al. (2016). In this vision, UAV-based cameras are used to collect informative images that document progress, productivity, construction quality, and safety requirements.

Geological and Geotechnical Engineering

The benefits presented by UAVs makes them potentially invaluable tools for geotechnical site reconnaissance and have been employed following recent events. These examples are covered in the section "Post-Disaster Reconnaissance." Terrestrial photogrammetric techniques have been established methods for imaging rock masses in 3D in structural geology (Bemis et al. 2014). Similarly, UAV-collected imagery has been used to characterize rock masses in 3D (Stumpf et al. 2013; Bemis et al. 2014; Salvini et al. 2015; Greenwood et al. 2016a; Vollgger and Cruden 2016). Emphasis has been placed on identifying and measuring discontinuities to quantify spatial variations and acquire geomechanical parameters (Greenwood et al. 2016a; Vollgger and Cruden 2016).

Stumpf et al. (2013) mapped surface fissures at the Super-Sauze landslide. The mapping efforts were used to better understand the mechanics of rock mass and the deformation of the slope over time. Lucieer et al. (2014) collected imagery of active landslide sites using an UAV. The imagery was collected over time and used to develop centimeter-scale 3D point clouds to measure landslide deformations. The accuracy of the image-based models was verified by differential GPS control points. Turner et al. (2015) used UAV-collected imagery and SfM photogrammetry to generate a time series of digital surface models (DSM) to measure landslide mass displacement over time. Salvini et al. (2015) used an UAV to collect images of rock masses in a marble quarry. The images were used to identify discontinuities and map them to identify the location and types of potential failures as part of a broad stability-monitoring scheme. Real-time stability analysis and identification of stability hazards is very useful for mine and quarry applications where slope cuts are designed at very low factors of safety. UAV-mounted cameras are powerful tools for mapping large areas rapidly and acquiring data in very difficult-to-reach locations for mapping geomorphologic features (d'Oleire-Oltmanns et al. 2012; Hugenholtz et al. 2013; Neugirg et al. 2016). Manousakis et al. (2016) and Saroglou et al. (2017) used SfM to document a rockfall caused by the 2015 Lefkada earthquake. Evidence in the UAV-generated DSM was used to identify the rockfall kinematic behavior (rolling, bouncing, etc.) and input into a rockfall analysis. These approaches of synthesizing UAV-based data with data generated from other sources is beneficial to better understand how UAVs can be integrated with current analytical practices. Clearly, the use of UAVs in geological and geotechnical engineering has been dominated by RGB imaging and relative displacement sensing, but other camera types, such as IR, have been used to investigate areas of geothermal activity (Harvey et al. 2016; Nishar et al. 2016).

There have also been data collection methods explored beyond imaging. While surface imaging is critical for many geotechnical projects, subsurface exploration is necessary. For example, Fernandes et al. (2015) used UAV-collected images to complement ground penetrating radar (GPR) surveys of outcropping carbonate rocks to better understand karst features in GPR images. Utilizing an UAV platform for additional data collection or test execution is of great interest and has only been explored on a very limited basis. Zekkos et al. (2014) demonstrated a proof-of-concept test of UAV-enabled seismic surface wave methods. The UAV dropped a weight used as the impulsive source for multichannel analysis of surface waves (MASW) which is used to estimate a shear wave velocity profile. Shear wave velocity profiles are useful for estimating liquefaction susceptibility, seismic site response, and mapping subsurface structure. The small-scale test was performed by Zekkos et al. (2014) in an indoor sand pit and an outdoor site. Greenwood et al. (2016b) used an UAV to introduce an impulsive source to a 2D geophone array placed on a concrete surface at an indoor flight facility. Geophone time histories were used to back-calculate an estimate of the source position relative to the array. Wood et al. (2016) conducted preliminary testing of an airborne magnetic survey with an UAV. Magnetometers were mounted to the wingtips of a fixed-wing UAV and flown in a grid pattern. Aeromagnetic surveys performed with UAVs have some particular challenges, such as magnetic anomalies generated by aircraft components (Forrester et al. 2014). Greenwood et al. (2018) expanded on work conducted by Zekkos et al. (2014) and Greenwood et al. (2016b) for introducing an impulsive source to the ground surface for MASW testing. Generating the signal using the UAV-dropped weight was found to have advantages over a conventional sledgehammer source. The UAV-dropped weight can introduce more energy which can enable deeper subsurface investigations. Surface wave generation by UAV is a fundamental component of developing an autonomous system for remote subsurface sensing and of value to the following subsection on post-disaster reconnaissance.

Post-Disaster Reconnaissance

In recent years, the engineering community has witnessed many natural disasters (e.g., earthquakes, landslides, tsunamis, and tropical storms) causing significant damage to infrastructure systems and loss of human life. When appropriate, teams of civil engineers perform costly reconnaissance studies to document structural or geotechnical damage and collect perishable field performance data of system behavior during extreme natural hazard events. Findings are then used to refine the scientific understanding of system behavior, so that design methods can be improved, and achieve greater system resiliency. Findings are also a critical input to decision making centered on recovery efforts. Data collection in these harsh operational environments presents many obstacles including ensuring personnel safety, perishable nature of field data, inaccessibility of many sites, and the challenges associated with acquiring physical measurements. UAVs have proven highly effective in mitigating these obstacles, as discussed subsequently. For example, the cost of hiring a helicopter for a few hours to perform site reconnaissance far exceeds the costs associated with purchasing several camera-equipped UAVs, assuming that helicopters are available at that time. The discussion to follow begins with damage to structures and infrastructure components, then considers landslide mapping, and finishes with UAV cooperation with search and rescue. For each of these topic areas, the presentation of past work with UAVs is presented in a chronological manner.

UAVs have recently been incorporated into teams of immediate post-disaster reconnaissance experts (PEER 2014; Rollins et al. 2014; Hashash et al. 2015a; El Mohtar et al. 2016; Zekkos et al. 2016). In all these cases, small UAVs were flown equipped with conventional optical cameras. Images were used to develop 3D point clouds of a variety of targets ranging in size. Having been used for a number of years as part of post-event reconnaissance, operational frameworks for reconnaissance planning and execution using UAVs are emerging. For example, Murphy et al. (2015) provided a review of planning and execution methods for UAV-based reconnaissance, and also highlighted some of the complications involved in performing immediate post-disaster reconnaissance with UAVs, such as coordination with search-and-rescue teams. Murphy et al. (2015) emphasized the importance of accurate geotagging of images and maintaining high-resolution real-time video feeds during flight. Data archiving was also identified as a major issue in UAV-based data collection. While UAVs have the ability to collect and transmit different types of data in real time, the communication networks for disseminating the information to stakeholders and decision makers still requires further development (e.g., Duncan and Murphy 2014).

UAVs have been vital to collecting perishable data immediately after high-wind, flood, and seismic events. For example, Adams et al. (2012) conducted UAV-based image collection of tornado-induced damage in Alabama and demonstrated that the UAV could collect aerial images with a sub-centimeter ground sampling distance (GSD) which was an improvement over what could be done with National Oceanic and Atmospheric Administration (NOAA) satellite images. While photographs were taken using UAVs, they were only used to qualitatively assess damage and to make distance measurements. As part of reconnaissance after the 2014 Iquique, Chile, earthquake, Rollins et al. (2014) collected photos of a damaged pier. Using Agisoft PhotoScan (Agisoft 2016), a commercial SfM package, point clouds of the pier with a reported absolute resolution of about 5.5 cm were used to demonstrate the potential of UAV-collected imagery in a postearthquake setting. The reconnaissance team in Iquique, Chile, also used an UAV-mounted camera to collect images and produce 3D models of the Tana bridge and liquefaction-induced lateral spreading adjacent to the Tana river. The resulting models had absolute resolutions of about 1 cm and were used to accompany field observations of lateral spreading. The Pacific Earthquake Engineering Research Center (PEER) also used an UAV as part of reconnaissance after the 2014 South Napa, California, earthquake (PEER 2014). The team executed both manual and semi-automated UAV surveys to collect imagery of a variety of sites including damaged buildings in urban and rural settings, suburban residential areas, bridges, and a water tower. Collected imagery was used to develop 3D point clouds using SfM photogrammetry. The 3D models were, in several cases, coupled with terrestrial LiDAR surveys. Terrestrial LiDAR surveys are the standard practice for the acquisition of relative displacement measurements in post-disaster scenarios. UAV-collected images were used to survey areas inaccessible to the terrestrial LiDAR scan, such as building roofs. LiDAR scans were also used to provide scale for the photogrammetric models obtained from the UAV imagery. Torok et al. (2014) used an UAV to deploy a ground-based robot used in a post-disaster structural crack detection scheme in concrete structures. SfM was used to reconstruct three-dimensional models of concrete structural elements with major cracks imaged and their width and depth profiles captured. Zekkos et al. (2016) documented the geometric characteristics of four damaged infrastructure projects by deploying a low-cost UAV within 48 h following three different natural disasters in Greece. A point cloud model using SfM software package Pix4D version 3.2 (2017) was derived for a damaged port pier in which millimeter- to centimeter-sized crack openings could be measured. A bridge failure due to scour was also mapped showing the settlement, rotation, and dip of a bridge pier. A dam failure and the downstream flooded area were also mapped.

UAVs are especially valuable tools for difficult-to-reach sites following disasters due to terrain or simply due to their geographic size. For example, Niethammer et al. (2012) collected imagery of the Super-Sauze landslide near Grenoble, France. The landslide deposit was thoroughly mapped to identify key features. DTMs were developed using a close-range photogrammetry tool chain consisting of Vision Measurement System (VMS) (VMS 2010) and the dense stereo matcher Gruen-Otto-Chau (GOTCHA) (Otto and Chau 1989). The UAV-developed orthophotos were compared with older orthophotos of the landslide and were used to estimate daily average displacement rates. Murphy et al. (2015) employed multiple small UAVs in response to the 2014 Oso, Washington, landslide. UAV imagery was collected to address four priorities: low-altitude imagery of the riverbed, imagery of lower scarp section, imagery of upper scarp section, and mapping of potential access points. These imaging priorities allowed the UAV to critically assist with search-and-rescue operations. Mapping with the images allowed engineers and geologists to identify the possibility of additional ground movement and how to approach removing the debris. El Mohtar et al. (2016) collected close-range UAV-based imagery of the Kfarnabrakh landslide in Lebanon. A DSM of the site was generated using the collected imagery; the model had an absolute resolution of 10 cm. The model was then compared with the pre-failure geometry synthesized from satellite images. Geometries were co-registered on the basis of notable fixtures such as buildings. The comparison yielded estimates of the ground surface retreat and volume of the failure mass. Hashash et al. (2015a) used a low-cost, commercial UAV in Nepal after the 2015 Gorkha earthquake. The UAV was used to collect an extensive amount of imagery of earthquake-affected sites, most especially landslides and hydropower facilities. Imagery was a critical aspect of qualitative assessment of geotechnical system performance during the Gorkha earthquake. Greenwood et al. (2016a) also collected UAV-based imagery of seismic-induced and typhoon-enhanced landslides caused by the 2015 Gorkha earthquake. Three-dimensional point clouds of the landslides were created using the commercial SfM software package Pix4D; point clouds were used to define landslide surface geometries and identify rock mass failure modes. The exposed landslide rock mass imagery was segmented and geomechanically characterized on the basis of fracture spacing in the 3D point cloud.

As previously mentioned, sites affected by extreme events can pose serious risks to search-and-rescue personnel and scientific investigators. Risks may even include radiation, such as with the 2011 Fukushima nuclear disaster (Duncan and Murphy 2014). Use on dangerous sites is one area in which UAVs can play a major role. For example, Duncan and Murphy (2014) demonstrated the use of autonomous radiation-detecting UAVs at a simulated building collapse. It was found that UAVs could perform a radiological survey more efficiently than a ground-based reconnaissance team, while reducing the radiation exposure to the team and reducing the number of team members required to perform the survey. The UAV was also used as part of decision-making processes in the field by rapidly transmitting data to all human parties.

Post-disaster scenarios are multifaceted problems, as demonstrated by the many applications of UAVs discussed previously. Kochersberger et al. (2014) developed an autonomous helicopter UAV capable of performing several post-disaster reconnaissance tasks such as ground-based robot deployment and retrieval, radiation measurement and source localization, and terrain mapping. Michael et al. (2012) coordinated ground-based robots and UAVs to map the interior of earthquake-damaged structures and to identify access paths for first responders. They emphasized the need to not only define conditions for autonomous vehicles to interact with each other, but for the vehicles to interact with humans (such as search-and-rescue personnel) during operation. The development of unmanned vehicle platforms for post-disaster reconnaissance has taken different approaches: development of platforms to perform many, if not all, tasks (Kochersberger et al. 2014) or development of multiple platforms collaborating to perform tasks (Michael et al. 2012). It may be unclear which approach will become most prevalent in the future. UAV collaboration certainly indicates greater data collection speed, as a single, flexible platform consolidates the risk of UAV interactions with other vehicles and humans. The authors of this paper expect teams of UAVs will become the preferred approach including swarms and platforms performing complimentary functions that may only interact virtually.

The fundamental aspects of UAVs, chiefly mobility, make them ideal tools to be leveraged for post-disaster efforts including search and rescue, rapid risk assessment, hazard identification, and data collection. Figs. 8(a–c) show the current post-disaster reconnaissance paradigm of initial reconnaissance, deformation documentation, and in situ testing. For example, following an earthquake, sites of interest must be identified often from traveling on available roadways. The deformation of structures and geostructures is ideally documented by terrestrial LiDAR scans from limited perspectives; however, there are cases in which this is not always true. Even now, hand measurements are commonplace as the primary method of documenting displacements. Site characterization is typically limited by site accessibility and available resources. Equipment is difficult to mobilize in earthquake-affected regions. Additionally, the perishability of data dramatically limits both the number of sites that can be investigated and the scope of individual site characterization plans.

Figs. 8(d–f) show an envisioned paradigm in which integrating UAVs has transformed the reconnaissance, documentation, and testing phases of the reconnaissance paradigm. Initial reconnaissance is hindered by a lack of information. Ground-based travel is often obstructed, helicopters are costly or unavailable, and satellite imagery may be too coarse, unavailable, or obstructed. The ability of UAVs to perform broad, rapid initial reconnaissance and geometrically document sites has already started to influence post-disaster

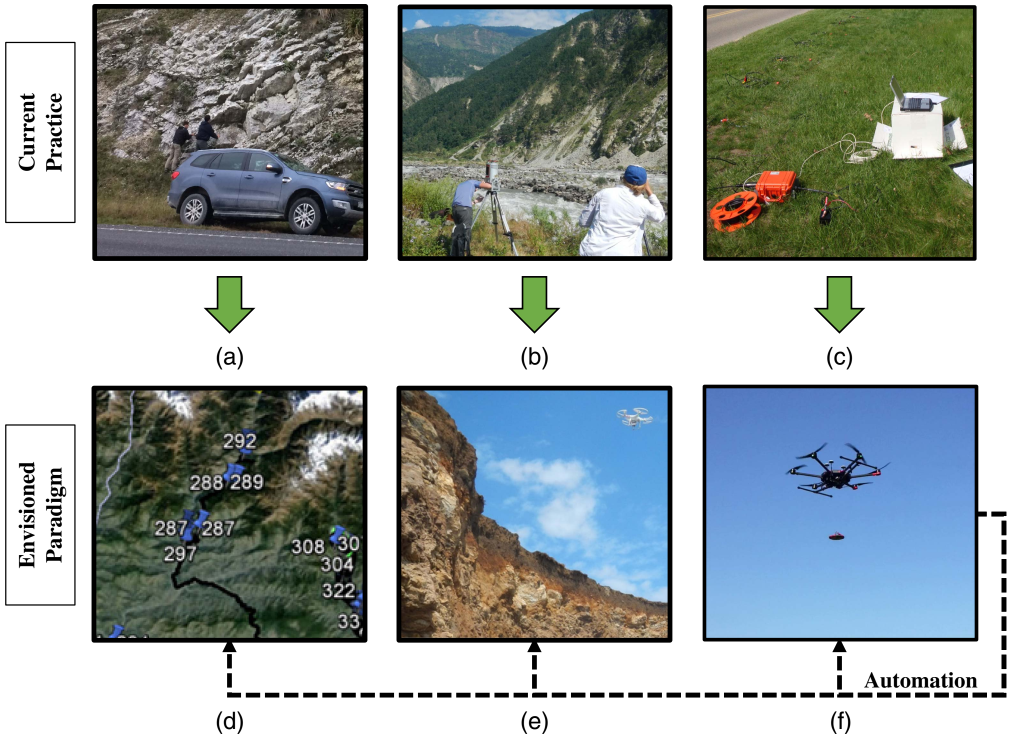

Fig. 8. Current practice consists of (a) manual reconnaissance requiring site access; (b) deformation measurements; and (c) manual site characterization processes. The UAV envisioned paradigm consists of (d) UAVs gaining access to sites; (e) collecting deformation data using SfM or LiDAR; and (f) UAV-based site characterization through actuation and automation. (Images by Dimitrios Zekkos and William W. Greenwood.)

schemes. Specific cases have been identified in this section that demonstrate ways UAVs can be effectively used in the first and second stages of reconnaissance. Little work has been done to alleviate the factors affecting the rate and scope of site characterization efforts. UAV integration with reconnaissance has obvious potential to transform the paradigm other than boosting data collection. There are clear opportunities to develop automated frameworks for continuously performing all three stages of reconnaissance as new information is acquired. This will help reduce site selection bias by improving the depth and breadth of documented sites which has a direct impact on the resilience of critical infrastructure systems.

Lessons Learned and Considerations for UAV-Based Infrastructure Investigations

This section outlines considerations for applying UAV-based inspection and data collection to a variety of infrastructure types. The types of infrastructure discussed is not exhaustive but is intended to provide useful insight that may be applied to applications not explicitly stated. The authors of this paper also provide some examples of lessons learned while using UAVs during their own research efforts.

Infrastructure-Specific Considerations

Table 3 contains eight examples of hard infrastructure in which UAV-based inspection and data collection is of interest. This is not an exhaustive list and the categories could even be further specified (e.g., paved versus unpaved roads, truss versus cable-stayed bridges) because considerations will vary within a category. For each of the categories in Table 3, the relative risk, consequences of an UAV malfunction, and likelihood of undesirable human interaction while investigating the different types of infrastructure are rated. These are relative ratings meant to allow readers to make general comparisons between the examples, but factors such as current usage (e.g., active highway) will increase risk.

The risk of UAV failure will additionally vary as a function of other conditions such as wind and current use by humans (i.e., vary between low and high). For example, bridges and power lines expose the UAV to the greatest possibility of gusting winds. Clearly, even if not gusting, wind is still an important consideration. The UAV's response to wind gusts diminishes as the maximum payload capacity is reached. If the UAV is carrying sensing hardware or delivering sensor nodes near maximum payload capacity, the risk of approaching a structure within a few meters increases.

The potential for undesirable human interaction with the UAV also increases risk and varies depending on the current usage and proximity to population centers (e.g., active highway versus a closed road). Long-range railroad or pipeline inspections carried out in rural areas are very unlikely to involve human interaction. In addition to UAV interaction with humans, the effect of humans on collected data should be considered as well. For example, SfM bundle adjustment typically contains an algorithm to filter moving objects from sequential images, such as a person walking through the camera view. If there is high risk of humans entering the UAV path, collision avoidance and possibly human identification features will be important safety components for mitigating consequences. The consequences of UAV malfunction, such as uncontrolled flight or rotor failure, will also depend on whether the UAV can cause damage to the operation of the facility. For example, malfunction while inspecting power lines could require costly repairs in dangerous conditions and cause service interruptions for consumers.

Different infrastructure types present conditions in which many of the previously discussed UAV features (software and hardware) will be of particular interest. Table 3 lists some of the non-universal

Table 3. Infrastructure-specific considerations for data collection and inspection

Infrastructure type	Relative risk	Consequences of UAV failure	Likelihood of human interaction	Platform types	Non-universal UAV features or functions	Potential sensors
Roads	Moderate	Moderate	High	Multirotor, fixed-wing	Subsurface sensing	Camera, LiDAR, infrared
Bridges	High	High	High	Multirotor	Collision avoidance, precision positioning, vertical camera	Camera, LiDAR, infrared
Levees and dams	Moderate	Moderate	Low	Multirotor, fixed-wing	Subsurface sensing	Camera, LiDAR, infrared, SAR
Landfills	Low	Low	Low	Multirotor, fixed-wing	Subsurface sensing	Camera, LiDAR, infrared, gas, SAR
Power lines	High	Very high	Low	Multirotor	Collision avoidance, precision positioning	Camera, LiDAR, infrared
Pipelines	Low	Low	Low	Multirotor, fixed-wing	Long-range communication	Camera, LiDAR, infrared
Tunnels	High	Low	Moderate	Multirotor	Collision avoidance, satellite-free navigation, vertical camera, subsurface sensing	Camera, LiDAR, infrared
Railroads	Low	Low	Low	Multirotor, fixed-wing	Long-range communication	Camera, LiDAR, infrared SAR
Canals and irrigation systems	High	High	Moderate	Multirotor, fixed-wing	Sample collection	Camera, LiDAR, infrared, gas

features or functions that would be of interest, or essential, for UAV operations. Many other functions exist and are often of interest to any infrastructure application, such as wireless sensor interrogation. For bridge inspection, a camera or LiDAR system mounted on top of the UAV will be useful for inspecting structural components on the underside of the bridge. Close-range (i.e., within a few meters) inspection and flight around or under complicated 3D structures places emphasis on the need for collision avoidance systems. Satellite-free navigation is essential for operations at indoor or underground facilities such as tunnels. However, there are other cases of GPS-denied environments outside of such facilities. For example, while mapping a rockfall-damaged construction site in Nepal at the bottom of a steep valley, sufficient satellite connections could not be obtained by the UAV. Without the implementation of a robust navigation architecture in the absence of satellite access, the mapping procedure could not be carried out optimally, which reduced the scope of the data collection.

Key Lessons Learned from UAV-Based Imaging

In this subsection, five key domains of lessons learned by the authors of this paper are discussed. The domains are flight adaptation, regulatory environments, data management, hardware maintenance, and integration with other platforms. This subsection is intended to convey key points for consideration by new and proficient UAV users alike.

Flight Adaptation

The potential for flight plan interruptions must also be considered. One potential cause of abruptly changing flight parameters that is often overlooked is the interaction of the UAV with wildlife. As an example, for one of the landslides investigated by Greenwood et al. (2016a), the flight mission for SfM was planned so that higher resolution imagery could be collected of areas where different failure modes were observed. However, images were collected from only as close as 40 m from the inspection target at the top of the slope, which was insufficient for geomechanical characterization. This was due to the flight mission being abandoned because of aggressive interaction with a hawk that was nesting near the top of the slope. UAVs can also provide on-demand qualitative data that is transformative for infrastructure hazard assessments. Zekkos et al. (2017) used an UAV to track the path taken by a debris flow and identify landslides that contributed to the debris flow material during an, initially, unplanned mission. The UAV did not collect images for quantitative analysis of these landslides but was used to provide a unique perspective where satellite images of the area were distorted or had low resolution.

Regulatory Hurdles

As previously mentioned, the regulatory environments around UAVs will vary significantly between countries. In preparation for operating an UAV in Nepal, acquiring proper permissions and understanding flight limitations spanned months. Operators should consider the time that may be required for regulatory approval and the potential ramifications of testing delays. Regulatory requirements may also vary at different levels of government or within institutions. The authors of this paper have performed numerous flights requiring approval from an established internal review committee at the University of Michigan. Peer review of mission plans is beneficial for learning new approaches and drawing attention to potential hazards or obstacles.

Data Management

When collecting images for vision applications using UAVs, it is important to consider the amount of data being generated. Video recorded in 4K resolution can generate data at about 0.4–1 GB per minute (depending on framerate, bitrate, codec, etc.). The storage device (e.g., microSD card) must have sufficient space for the imagery and also write the data at a sufficient rate. The total size of vision data can accumulate quickly and storage of such data is expensive. Adapting flight plans to minimize the number of images and image resolution is recommended to collect data more efficiently and reduce storage or processing costs. As civil infrastructure applications begin to explore real-time decision making involving data transmission and onboard data management, unnecessarily large data volumes become a concern. Scalable data storage architectures for UAVs will become important especially for multisensor platforms used for infrastructure inspections.

Hardware Maintenance

UAS contain many components that require routine maintenance, including software (firmware, drivers, etc.). Battery resource management capabilities are contained in many basic UAV flight control software packages including those for monitoring the long-term health of batteries. The most critical short-term maintenance consideration is the health of multirotor propellers. Platforms with six or more rotors with current flight controllers have some redundancy against motor or propeller failure. Quadrotors have no redundancy against motor and propeller failure. Propellers should be inspected prior to each flight for signs of stress, particularly near where the blades connect to the point of rotation. The propeller connection to the motor, such as screw threads, will wear over time. Another long-term consideration for the UAV's onboard hardware is the accumulation of dust and particles typically during takeoff and landing.

Integrating with Other Platforms

Integration of UAV-collected data, especially vision, with other data types and workflows was identified as an important research direction in this review. Long-term storage of data, such as site surveys, must be managed in such a way to maintain data accessibility. Rapid withdrawal of past topographic surveys to compare with recently collected data, for example, may be desirable. GIS should be used to document the various sets, or types, of geospatial data collected by UAVs for infrastructure applications (e.g., bridge or dam inventories). GIS can act as the unifying platform or combining different pieces of data and is one reason why robust georeferencing of data sets is important. Positioning errors generate uncertainty that is propagated through further analyses and into other data sets if they are synthesized.

Summary, Conclusions, and Recommendations of Future Work

This paper reviewed novel research focused on the application of UAVs for civil infrastructure systems with emphasis placed on recent, transformative advances in civil engineering. In general, the main thrust of UAV efforts in data collection and processing has been with imaging. Imaging methods such as structure from motion and stereo vision have been established for an extended period of time. The robustness of established imaging methods and the popularity of UAVs with onboard cameras has led to imaging being the early focus of research efforts. This has also led to new imaging methods being developed largely for vehicle automation, such as vision-based localization. Recent discussions in the US about integrating UAVs in the national airspace at night raises some interest in investigating nonvision sensors for autonomous navigation and obstacle avoidance such as sonar and LiDAR. In recent years, research efforts in data collection and processing have extended beyond imaging methods to include other sensors such as gases, biological pathogens, and SAR [Leuschen et al. (2014), Lu et al. (2015), and Rossi and Brunelli (2016) among others]. However, these transformative efforts are often occurring outside of civil engineering but are certainly of interest to applications involving those sensors (e.g., modeling air quality, detecting methane emissions, and ground displacements).

In civil engineering, UAVs are already used for post-disaster response, structural damage assessment, infrastructure inspection, rock characterization, mining, magnetic surveys, seismic geophysical methods, and construction monitoring. The most interesting UAV research developments have involved incorporating UAVs into high-functioning complex systems capable of interacting with humans and interfacing with data streams (e.g., Murphy et al. 2015). UAVs will become powerful autonomous systems having the ability to develop an action plan, collect data, process data, perform computations, analyze results, and make next-step decisions. These components of autonomous UAV systems are being explored individually. However, more efforts into incorporating all of these components into fully autonomous systems are needed (e.g., Song and Jo 2017). The authors of this paper have identified the following six knowledge gaps that are expected to, or have already, become major research thrusts:

- Integration with workflows and data fusion: Many cases of UAVs being used to develop high-quality surface models (DEM, mesh, point cloud, etc.) have been documented. Few examples exist of these outputs describing surfaces being integrated with established workflows, or advancing workflows. The potential of rich surficial information produced by UAVs is well understood, but more implementations are of interest. For example, Hackl et al. (2018) developed surface models via UAV and used them in hydrodynamic modeling of flow under a bridge for risk assessment purposes.
- Autonomous frameworks: Many applications have had success developing new automated workflow components. The connection of the components into a complete workflow is typically underdeveloped. While we are currently not at a point at which fully autonomous UAS can be utilized due to a variety of factors that extend beyond scientific and technological limitations, developing the frameworks behind their development is important. Developing and implementing autonomous frameworks with UAVs faces additional nonscientific challenges. Researchers and practitioners must remain open and communicative as regulatory environments develop. Public outreach will be critical to the development of work in this domain, particularly with the current distrust of autonomous systems in the general public.
- Subsurface sensing systems: As has been noted in this review, the primary focus of UAV-based sensing has been on surface model development via remote sensing. UAVs are establishing themselves as a critical remote sensing tool that are highly adaptable to a range of sensors used at different spatial and temporal resolutions. The work that has been done on UAV-based sensing of below-surface features is limited. In this case, the surface could be a structural component, the ground, or ice. The authors of this paper have noted examples of geophysical methods that have already been established on other aerial platforms being implemented with or considered for use with small UAVs such as magnetic surveys, GPR, and surface wave methods. For geo-infrastructure applications, subsurface sensing is necessary and one of the major limitations is cost of mobilizing equipment and accessing remote or dispersed sites.
- Swarms and UAV cooperation: As UAVs become integrated in spaces occupied by other aircraft, and inevitably other UAVs, methodologies for managing the interaction, intended or otherwise, between UAVs is critical. Research into groups of cooperating UAVs, or swarms, has expanded greatly in recent years. While this topic is not covered in this review, it is gaining significant traction outside of civil engineering. UAV swarms may perform the same basic operation simultaneously, such as aerial surveying, or perform complementary operations, such as sensor placement and interrogation.
- Interfacing with humans: Some cases of human–UAV interaction in the fields of construction management and post-disaster reconnaissance have been identified in this review. These studies have generally concluded that human–UAV interaction is an important direction for research. The interactions of interest can, similar to multi-UAV interactions, be intentional or unintentional. The interactions also do not have to occur in physical space, they can be virtual. One component of developing fully autonomous UAS is understanding how to integrate human cognition for decision making. An early step in that direction would be to have humans decide the next UAV operations in real time, such as in a post-disaster scenario to select sites of interest and in

situ testing locations. This pseudo-training data could help construct the foundational autonomous frameworks.

- Actuation of infrastructure: The authors of this paper identified physical actuation of infrastructure components as an important research topic. Limited work has been performed involving physical interaction of UAVs with civil infrastructure. This physical interaction could include deployment of wireless sensor nodes or a stimulation of an infrastructure component such as modal analysis of a structure. Within the section "Lessons Learned and Considerations for UAV-Based Infrastructure Investigations," the authors noted in Table 3 that subsurface sensing, which would often involve actuation, is of interest to several types of infrastructure components and could be used to detect subsurface hazards (karsts, liquefiable soils, etc.) or visualize infrastructure systems such as landfills, levees, and dams.

Developments in UAV autonomy offer an opportunity to develop platforms to approach some of the multifaceted problems of infrastructure systems. Challenges exist from social and political perspectives as well for the integration of UAVs with science and engineering fields including civil infrastructure projects (Straub 2014; Boucher 2015; Bakx and Nyce 2016).

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