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Drone-based bridge inspections: Current practices and future directions

Tommaso Panigati [a,*], Mattia Zini [b], Domenico Striccoli [c], Pier Francesco Giordano [a], Daniel Tonelli [b], Maria Pina Limongelli [a,d], Daniele Zonta [b]

[a] Politecnico di Milano, Department of Architecture, Built environment and Construction engineering, Piazza Leonardo da Vinci 32, 20133 Milan, Italy
[b] University of Trento, Department of Civil, Environmental and Mechanical Engineering, Via Mesiano 77, 38123 Trento, Italy
[c] Polytechnic University of Bari, Department of Electrical and Information Engineering, Via Orabona 4, 70125 Bari, Italy
[d] Lund University, Faculty of Engineering, John Ericssons väg 1, Lund, Sweden

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ABSTRACT

As transportation infrastructure networks continue to age, bridges have become critical components requiring monitoring activities to ensure safety and functionality. Inspections and Structural Health Monitoring (SHM) play a vital role in aiding decision-makers in maintaining structural integrity. Drones have gained popularity for bridge inspections because they offer enhanced safety, efficiency, and cost-effectiveness compared to traditional methods. This paper provides a multi-faceted review of existing research on drone-based bridge monitoring, focusing on equipment, inspection procedures, outcomes, the Internet of Drones (IoD), and associated communication technologies, exploring current limitations, future directions and potential advancements. In the near future, it is expected that the application of computer vision techniques to drone-captured imagery will expand the possibilities for automated surface damage detection and extraction of dynamic structural features. The main challenges lie in the integration with IoD, and the standardization of the procedures, paving the way for fully automated drone-assisted inspections.

1. Introduction

Bridges are critical assets in transportation networks, yet they are inherently vulnerable to various factors that can lead to traffic limitations, closures or even catastrophic collapses. Typically, the causes of bridge collapses are categorized as enabling and triggering causes [1]. Enabling causes refer to internal deficiencies such as design flaws, poor detailing, construction errors, insufficient maintenance, or the use of substandard materials, which compromise the bridge's capacity. Triggering causes, on the other hand, involve external events like natural disasters, collisions, or overloads that place demands exceeding the bridge's capacity and initiate the collapse [2]. The consequences of bridge collapses can be catastrophic, profoundly impacting human lives, economies, societies and the environment. Replacing existing transportation infrastructures is impractical due to the high environmental and societal costs [3]. Therefore, monitoring activities - including periodic inspections and Structural Health Monitoring (SHM) - are essential for proactive assessment and timely interventions to maintain safe operation [4].

The primary method for assessing bridge conditions is through inspections performed by dedicated personnel, consisting mainly of visual inspections, that can range from quick surveys to detailed examinations. They can also be supplemented with non-destructive and destructive tests for a more comprehensive understanding of a bridge's condition.

However, traditional inspection methods have significant limitations. Accessibility issues often prevent inspectors from reaching hidden areas of bridges, resulting in incomplete assessments. Subjectivity is another concern, as the outcomes can vary greatly depending on the inspector's experience and judgment. Inspections are performed at set intervals, which might not align with the onset of damage, potentially leading to delayed interventions. Detailed and frequent inspections, especially for structures in poor condition, can be costly and resource intensive. Furthermore, conducting inspections on large bridges poses significant safety risks to the inspectors themselves.

In the last decades, contact-type SHM systems - composed of several hardware components such as sensors, cables and data acquisition systems - have been developed to provide automatic and continuous information about structural health conditions [5]. However, traditional approaches based on contact sensing present some drawbacks. The cost

* Corresponding author.
E-mail address: tommaso.panigati@polimi.it (T. Panigati).

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of intensive instrumentation for a bridge can be high, making SHM systems typically installed only on a limited number of strategically important structures. Once a contact-type SHM system is installed on a bridge, its components are often not reusable for other structures. Additionally, components are prone to faults during extreme events, precisely when critical structural health information is needed most [6].

To overcome the limits of traditional monitoring systems, in recent years, the use of drones equipped with cameras and other sensors has gained increasing popularity as a complement to traditional monitoring methods. In the literature, numerous terms are used for drones, such as Unmanned Aerial Vehicle (UAV), Unmanned Aircraft System (UAS), Remotely Piloted Aircraft (RPA), and Remotely Piloted Vehicle (RPV). However, the term “drone” is used in this work due to its popularity in the scientific community and public [7].

Drone-based inspections offer several advantages over traditional methods. They provide a versatile and efficient means of data collection and monitoring and can perform detailed inspections, detect superficial damage, and even assess dynamic parameters, all while generating information that can be integrated into broader management systems for improved maintenance and decision-making. The large amount of information obtained from drone sensors, including high-quality videos and images, can be stored on memory cards inside the drone and later post-processed in the office or delivered directly to a ground/fly station deployed in the area of interest through a wireless communication system (e.g., MAVLink and 5G/6G) [8].

Drones can be deployed across multiple bridges, potentially covering entire infrastructure networks [9]; the mobility and modularity of drone systems allow for easy deployment and reuse on different structures. Drones can carry sensors in contact or proximity of the bridge, enabling thorough inspections of hazardous areas or hard-to-reach locations [10]. Utilizing drones for inspections significantly mitigates risks for human operators, including hazards such as falls, unstable environments, and exposure to dangerous conditions [11]. Inspections aided by drones are generally faster than traditional inspections [12]. Furthermore, drones are resilient to external factors that can impact traditional SHM systems. They operate effectively, regardless of power outages, theft, tampering, or vandalism [13].

Most drone-based monitoring strategies rely on the analysis of images and videos captured during inspections, utilizing advanced computer vision techniques. From the literature, two primary computer-vision approaches to bridge monitoring emerge. The first focuses on surface damage detection, using cameras to assess superficial damage conditions such as cracks, concrete spalling, and exposed reinforcements. The second performs vibrational monitoring using data from drone-capture videos and applying Operational Modal Analysis (OMA) techniques to identify modal parameters, such as frequencies and mode shapes. Furthermore, other approaches not relying on computer vision can be identified, as in the case of drone-based Non-Destructive Testing (NDT).

This paper aims to provide a comprehensive and updated review of the key aspects associated with the use of drones for bridge monitoring, from the current technology and methods to the most interesting case studies. Specifically, the contribution of this paper involves the integration of several different aspects of drone-based bridge inspection, encompassing equipment, inspection procedures, inspection phases, communication technologies and data elaboration. The paper includes the latest research results in the different fields, not only related to bridge monitoring but also to information engineering and aerospace engineering. As for Sections 2, 3 and 5, the search strategy involved three steps: (i) systematic research of papers through keywords, (ii) manual selection of relevant papers (iii) integration of literature results with cross-referenced papers and other relevant documents. In detail, the keywords *(drone OR uav) AND ((structural AND health AND monitoring) OR shm OR inspection) AND bridge* were used in Scopus to individuate the most relevant studies for the use of drones in bridge monitoring. From the systematic research, 736 papers were retrieved. After phases (ii) and (iii), 131 papers were included in this review. Regarding the selection of communication technologies, the literature search followed a two-step strategy. First, the communication technologies were selected based on their communication range. Accordingly, technologies were classified as wide-range and short-range communications. Wide-range communications can cover large areas, such as cellular technology, WiMAX, and satellite-based technologies. Instead, short-range communications, such as Zigbee and Bluetooth technologies, are instead used for relatively short distances. The second step was then linking the communication range to the application scenarios where drones are employed. More in detail, wide-range technologies are suitable for drone control, connectivity increase, relaying, and in general in emergencies or when drones are outside the range of direct links. Short-range technologies are exploited for different applications like flight control, real-time data acquisition, file transfer, device synchronization, low-power/low-cost communications, and drone localization [14]. The goal of this approach is to select the subset of technologies that can fit best the drone-based monitoring and inspection scenario which is the focus of this contribution.

Several review papers address the use of drones for inspecting and assessing the condition of civil structures. However, most of these papers contain only a few sections dedicated to drones within the broader context of robotic systems. A comprehensive review specifically focusing on the use of drones for bridge monitoring is still lacking. Tian et al. [15] explore robotic systems for structural monitoring, such as climbing robots, along with drones for tasks like vibration measurement and damage detection. Poorghasem & Bao [16] explore the use of drones for vibration measurement of civil structures. Zinno et al. [17], in their review of Artificial Intelligence (AI) applications for SHM, discuss the potential use of drones for displacement measurement and damage detection. Feroz & Dabous [9] review drone remote sensing applications with a focus on surface damage identification, along with safety regulations and data connectivity planning. However, they do not address vibration-based monitoring.

Given that most applications involving drones rely on image and video analysis, the field of computer vision is of significant interest to this study. However, most of the review papers on the topic do not have a specific emphasis on drones but are rather focused on fixed-camera setups. Although strictly connected to drone-based setups, fixed-camera setups do not face problems related to vibration caused by drone dynamics. Among these works, Ferraris et al. [18] review various computer vision techniques related to damage detection and visual modal analysis. Cha et al. [19] explore the integration of SHM with deep learning, including applications for surface damage detection. Sony et al. [20] describe smart-sensing technologies for SHM, including vision-based techniques. Spencer et al. [21] address computer vision applications for inspecting and monitoring civil structures, discussing both damage detection and dynamic monitoring. Zona [22] describes vision-based vibration monitoring techniques for different types of structures, including steel, concrete and masonry bridges, timber and steel footbridges and steel structures for stadiums. Luo et al. [23] review computer-vision-based applications for inspection and monitoring.

A key aspect of the use of drones for inspections is the need to transmit high volumes of data in real-time. This aspect is often overlooked in review papers dealing with drone-based monitoring which are mainly focused on the acquisition and processing of data to extract information about the structural condition. Recently the use of swarms of drones has gained traction as a technology to improve data collection. Communication within the swarm can greatly benefit from reliable and stable technologies. Moreover, the real-time transmission of heavy data such as high-quality videos from drones to distant locations is of particular interest for fully unmanned inspections. However, for heavy data transmission, there are particular network requirements. Based on the identified gaps, this review paper aims to cover the latest technological advancements concerning the following key topics: (i) damage identification approaches - specifically surface and modal-based - using computer vision techniques applied to data collected by moving cameras; (ii) integration of communication technologies to improve the operativity of single drones and drones swarms for bridge monitoring, in the framework of new developing communication standards such as 6G.

This review addresses the different phases of monitoring ultimately leading to decision-making: data acquisition, transmission and processing, as shown in Fig. 1.

First of all, the paper examines the technical equipment used in drone-based inspections, including the types of drones, sensors, and imaging technologies that are employed. It evaluates how these technologies contribute to the effectiveness of damage identification, such as recognizing cracks, corrosion, and other surface imperfections on bridge structures and highlights the tradeoffs imposed by the power requirements.

Furthermore, the review explores the methods and techniques for extracting modal parameters from captured data and discusses the challenges involved in data processing and interpretation. Modal parameters, such as natural frequencies and modal shapes, are critical for assessing the dynamic behavior and overall health of a bridge. Additionally, the review addresses various factors that affect the inspection process, including environmental conditions, flight planning, and data management. It also covers the integration of drone-collected information with Bridge Management Systems (BMS), highlighting how data from drone inspections can be used to inform maintenance strategies and prioritize repairs, thereby ensuring the long-term safety and performance of bridge infrastructure.

The paper is organized as follows. Section 2 describes the equipment that can be used for monitoring applications, considering limitations and potentialities. Section 3 illustrates inspection procedures, focusing on flying-path planning and optimization. Section 4 deals with the Internet of Drones and communication technologies, both related to the use of drones regarding security and operative limitations. Section 5 encompasses the main outcomes of inspections, namely superficial damage detection, vision-based operational modal analysis and other non-destructive testing outcomes. While in each section challenges and future perspective are presented for the topic of interest, Section 6 presents the most relevant concluding remarks.

2. Drones: historical background and equipment

This section explores the historical and technological evolution of drones, offering an overview of the origins and advancements that have shaped this technology. A summary table is provided, showcasing various drone models used in the reviewed studies, highlighting the range of drones applied across different inspection scenarios. The section also focuses on the key physical components of drones, with particular attention to the sensors and data acquisition systems essential for inspection tasks. Additionally, it outlines the critical characteristics and minimum requirements that a drone must meet to perform bridge inspections effectively, ensuring reliability, accuracy, and safety in operation.

2.1. Past and present

Drones have a long history, dating back to 1849 when Austrian soldiers used unmanned balloons filled with explosives during the Austro-Italian War to attack Venice [24]. However, large-scale use of drones began during World War I. In 1916, Britain developed the first winged aircraft drone, the "Ruston Proctor Aerial Target," followed in 1918 by the U.S. "Kettering Bug," an experimental aerial system with a flying bomb [25]. The 1940s saw the emergence of the first companies mass-producing drones in the United States. The modern drone era began in the 1960s, with both the United States and the Soviet Union developing drones primarily for military purposes [24]. The US military

Fig. 1. Drone-based bridge monitoring.

used drones for reconnaissance during the Vietnam War, and the Israeli military used them for surveillance and target practice in the 1980s [25]. By the early 2000s, drones became available for commercial use with DJI Technology and Parrot, revolutionizing the industry with the release of a quadcopter in 2010. The 12th Congress FAA Modernization and Reform Act (2011−2012), enacted by the Senate and House of Representatives of the United States of America, further facilitated drone integration into airspace.

While military applications have driven drone research for many years, drones are used today in various fields worldwide, including agriculture, environmental monitoring and conservation, public safety and security, emergency response, media and entertainment, logistics and delivery, real estate, energy, and scientific research. The use of drones in civil engineering, including inspections, is significantly increasing [9].

Table 1 summarizes the diverse uses of drones in bridge monitoring. It includes a range of drone models—both commercially available and custom-built—featured in the reviewed studies, providing detailed information on their sensor capabilities, payload capacity, flight duration, and communication protocols [16]. The specific characteristics of drone equipment, such as sensors, payload limitations, and flight times, are further elaborated in Section 2.2. The various monitoring applications and their outcomes are discussed in Sections 3 and 5, respectively. Notably, the column on Communication Protocols illustrates that, despite being branded under different names by manufacturers, these protocols are fundamentally based on the Wi-Fi standard, operating within similar bandwidths and frequencies. For a deeper analysis of drone communication technologies, refer to Section 4 of this paper.

2.2. Components and requirements

Drones are aircraft that can fly autonomously or be controlled by an operator on the ground. They are classified into various categories based on their functions, size, weight, number of propellers, aerodynamic flight principles, range, equipment, and cameras [23]. They feature rotating brushless motors, allowing for vertical take-off and landing, hovering, and carrying larger payloads. They can be either commercial or self-built.

The main components of drones, as shown in *Fig. 2*, include the airframe, propulsion system, communication system, navigation system, power system, and various sensors. The airframe, constructed from carbon or rigid plastic, must absorb and dissipate vibrations from the propellers and motors while being durable enough to withstand impacts. The propulsion system consists of motors and propellers, with four or more motors providing the necessary thrust for lift and maneuvering by varying their speeds independently, and propellers that generate lift and thrust, significantly influencing flight performance and efficiency. The communication system facilitates real-time control and telemetry data exchange between the quadcopter and the ground station through a radio-video transmitter and receiver. The navigation system includes the flight control unit, which processes sensor data and pilot inputs for stable and responsive flight, the Global Navigation Satellite System (GNSS) for location data enabling autonomous flight paths and position hold, and an Inertial Measurement Unit (IMU) comprising accelerometers and gyroscopes for maintaining stability and control. The power system is composed of a battery, power distribution board, and Electronic Speed Controllers (ESCs). Additionally, various sensors such as ultrasonic sensors, barometers, and optical flow sensors enhance the quadcopter's stability, altitude hold, and obstacle avoidance capabilities.

In drone development, the objective is to integrate a range of devices while ensuring that flight duration and versatility in carrying out different tasks are not compromised [41]. A variety of data acquisition devices can be attached to drones, enhancing their ability to conduct useful inspections. Some of the key devices include:

- **RGB image/video camera devices**. Essential for drones, these devices capture digital images and videos using vision sensors. Their

Table 1
Specifications of representative commercial and self-built drones, adapted from [16].

Model	Application	Commercial / Self-built	Sensor	Payload [kg]	Flight time [minute]	Communication Protocol	References
Parrot AR 2.0	Damage detection	Commercial	720p resolution with 30 fps camera	–	12	Wi-Fi	[26]
DJI Phantom 3	System identification	Commercial	1080p resolution with 25 fps camera	0.7	25	Enhanced Wi-Fi	[27]
PSI InstantEye	Displacement measurement	Commercial	720p resolution with 30 fps camera	2.25	30	Pico digital data link	[28]
DJI Phantom 3 pro	Vibration measurement	Commercial	2160p resolution with 24 fps camera	0.7	23	Lightbridge	[29]
DJI Phantom 4	Modal identification	Commercial	2160p resolution with 30 fps camera	0.8	30	Lightbridge	[30]
DJI Matrice 600 pro	Transverse displacement	Commercial	Laser Doppler Vibrometer (LDV)	2.0	25	Lightbridge 2 HD	[31]
DJI Spark	Vibration measurement	Commercial	1080p resolution with 30 fps camera	0.167	15	Wi-fi	[32]
DJI Mavic air 2	Vibration measurement	Commercial	4 K resolution with 30 fps camera	0.5	34	OcuSync 2.0	[33]
DJI M200	Cable force estimation	Commercial	2160p resolution with 60 fps camera	1.45	38	OcuSync 2.0	[34]
DJI Mavic Pro	Modal Analysis	Commercial	1080p resolution with 96 fps camera	0.5	27	OcuSync	[35]
DJI Mavic 2 Enterprise Dual	Modal Analysis	Commercial	4 K resolution with 30 fps camera	0.5	31	OcuSync 2.0	[35]
DJI Inspire 2	Crack identification	Commercial	Zenmuse X5S	0.8	27	Lightbridge	[36]
Assembled	Crack and moisture detection	Self-built	DSLR camera 8 K resolution +1D LiDAR	–	30	–	[12,37]
Assembled	Contact-based modal analysis	Self-built	No camera	0.38	5	FrSky 2.4 GHz	[38]
Assembled	3D reconstruction model. Crack, humidity and deformation detection	Self-built	DSLR camera with high resolution + LiDAR + LWIR sensors	5	–	–	[39]

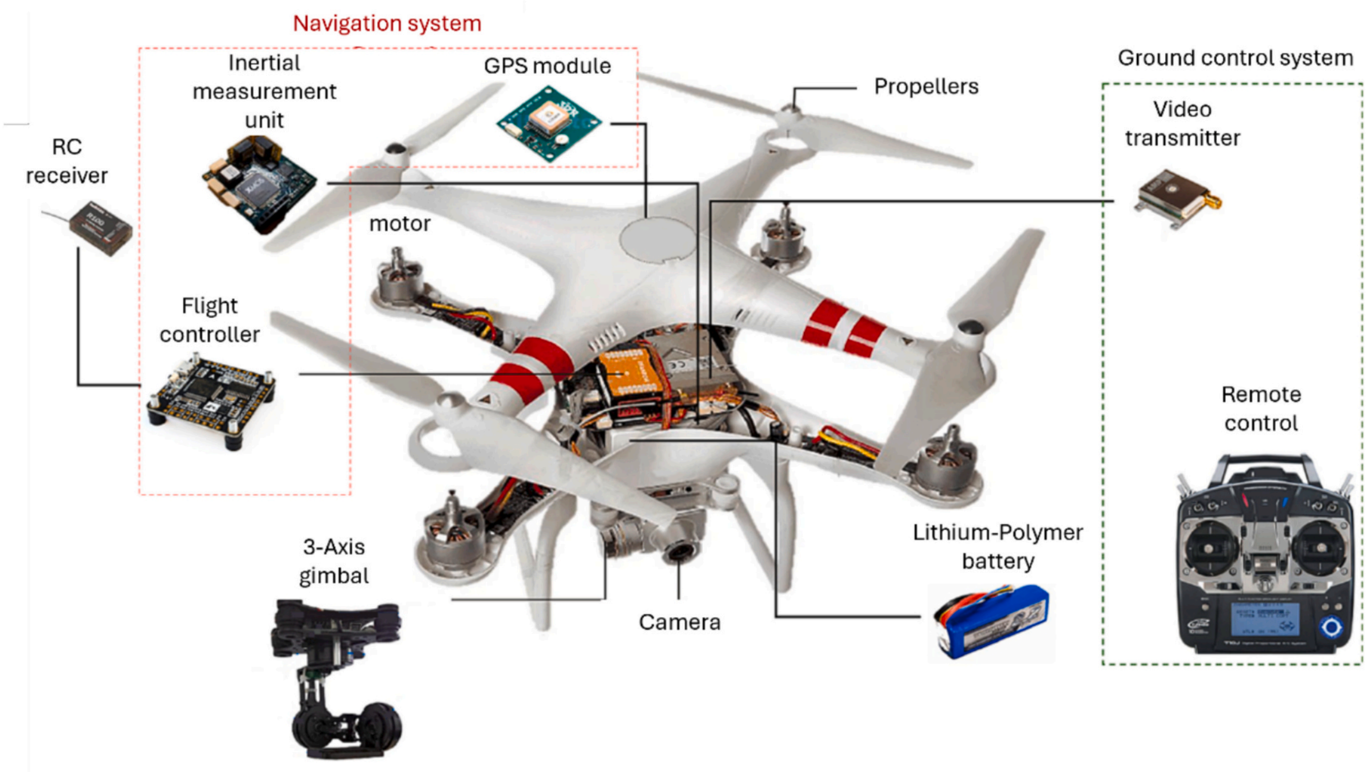

Fig. 2. Representative drone equipped with different components [16].

lightweight and compact design enables easy attachment to drones, making them well-suited for tasks such as surface damage detection. Advanced models, such as RGB-D sensors, further enhance this capability by recording pixel depth information, which supports the 3D reconstruction of infrastructure (Fig. 3 a).

- **LiDAR (Light Detection and Ranging) sensors**. LiDAR sensors use laser pulses to measure distances from single points with exceptional speed, often scanning thousands to millions of points per second. This rapid data collection allows for the creation of detailed 3D point clouds, which can reveal surface damage such as cracks and delamination in concrete structures (Fig. 3 b).
- **Thermal cameras**. Equipped with infrared sensors, thermal cameras detect temperature surface variations, revealing hidden structural issues like insulation problems or water leaks (Fig. 3 c).
- **NIR (Near Infrared) sensors.** Although costly and less commonly used, NIR sensors combine RGB images with infrared data. By analyzing different wavelengths, NIR sensors can identify surface damage such as moisture infiltration or concrete spalling, making them valuable for more specialized inspections.

When considering the minimum requirements for drones in bridge inspection, a balance must be struck between competing needs. The weight of the drone is a critical factor that directly impacts flight autonomy as heavier drones can fly for less time. Ideally, drones should have a flight time of at least 20 to 30 min per battery charge to ensure effective inspection operations [42]. A lighter drone design can extend flight times and reduce the risk of overheating motors and electronics. On the other hand, heavier drones tend to perform better in moderate wind conditions, requiring the drone to withstand wind speeds of at least 10 m/s to minimize vibrations and sudden movements caused by air turbulence [43]. In Europe, drones weighing less than 249 g can be flown without a license, which also extends their operational efficiency [44]. Perez Jimeno et al. [45] utilized four drone batteries for a total of 60 min to capture 536 photos for a photogrammetric reconstruction of a 28 m long bridge. The payload, which includes attached cameras, sensors, and other essential monitoring equipment, also increases the drone's total weight and reduces autonomy. However, the presence of a high-quality camera is essential for vision-based monitoring applications. The drone should be equipped with a high-resolution camera (at least 2.7 k to 4 k) and zoom capabilities. Zoom capabilities are equally

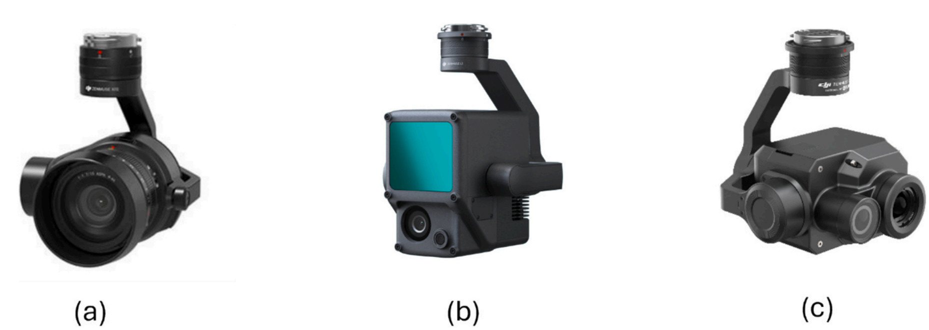

Fig. 3. Variety of data acquisition devices. a) DJI Zenmuse x5s camera; b) DJI Zenmuse L1 LIDAR sensor; c) DJI Zenmuse XT2 Infrared sensor.

important, allowing for close-up inspections of structural features and enabling the detection of small defects from a distance. High resolution is particularly critical for recording sub-millimetric displacements, which are essential for visual modal analysis.

In addition to a high-quality camera, an active gimbal is a standard feature in most drones, playing a crucial role in stabilizing the camera. The gimbal not only isolates the camera from the drone's vibrations, which is vital for capturing smooth, clear videos but also often includes the ability to rotate the camera upward [42]. The effectiveness of the camera and gimbal setup is further enhanced by navigation systems. Such a system should provide precise stabilization with minimal vibrations, ensuring that the drone can maintain a steady position during inspections. Furthermore, the navigation system should be capable of obstacle avoidance and support autonomous movement to predetermined points of interest, allowing for efficient and safe data collection even in complex environments.

2.3. Future perspectives in drone technology

In this section, on-field applications of drones for bridge monitoring were shown. It is remarked that Table 1 presents applications from academic literature and does not aim to represent drones currently available on the market. Therefore, recently developed drones, such as DJI MINI 4 PRO or POTENSIC ATOM SE, are not included, as they have not yet been referenced in published studies. However, the authors believe that lightweight drones of this nature will play a significant role in drone-based inspection, offering a low-cost and user-friendly solution for bridge monitoring. Additionally, the drone industry is making advancements in heavy-lift drones, which will enable the transportation of heavier payloads, thereby facilitating the use of more sophisticated sensing devices. Therefore, cutting-edge developments in the drone industry, especially those concerning payload capacity, flight duration, remote control and hovering stability, are expected to provide bridge inspector with a wide range of tools. However, being the drone industry vibrant and in constant change, it is difficult to forecast the speed and market penetration of these advancements, even in the close future, also considering the particular relevance of the regulatory process in fostering practical applications of innovations in the field.

3. Inspection procedures

This section offers an examination of drone inspection procedures, organized into two main parts. The first part examines the various phases of drone inspections as reported in the literature, aiming to establish a comprehensive guideline for obtaining key parameters across different survey methods. This analysis provides a structured approach for effectively conducting drone inspections.

The second part focuses on critical issues and considerations highlighted by different authors in their studies. These include flight path optimization, distance between the drone and the target, flight speed, timing of the flight, and battery level and condition. By consolidating these considerations, this section highlights the challenges and best practices associated with drone-based inspections.

3.1. Inspection phases

Procedures for drone inspections typically vary based on factors such as the type of structure being monitored, the specific drone model utilized, the components under analysis, and the methods employed. Kim et al. [12] outline a drone-based bridge inspection procedure divided into three distinct phases: (i) Pre-Inspection Phase, (ii) Main Inspection Phase and (iii) Post-Inspection Phase. Each phase is further subdivided into specific steps that cover all operations to be performed before, during, and after the inspection. These phases, detailed below, also align with similar procedures observed in numerous other studies reviewed for this paper.

The Pre-Inspection Phase involves a thorough examination of target bridge information, analyzing all historical inspections and existing reports. The insights acquired during this stage empower the pilot to devise flight strategies, particularly in situations of restricted bridge accessibility. If prior information is lacking, a preliminary flight may be conducted to create a 2D/3D model of the structure. Additionally, an on-site risk assessment must be performed, and current restrictions in the area should be verified using authorized air traffic maps [46]. It is also essential to thoroughly inspect the drone and camera settings before each first flight. Eventually, the inspection program and flight path are planned.

The Main Inspection Phase involves the on-site inspection using drones. In the case of surface damage detection, it is advisable to initially capture an overview of the entire bridge and then acquire detailed information on each structural and non-structural component [44]. The inspection can be carried out automatically or manually, depending on whether it follows the preliminary instructions of the flight planning or relies on the control capabilities of an operator pilot [13]. To determine the natural frequencies and vibration modes, the drone must be positioned in a hovering flight at specific points and distances from the bridge. The drone needs to remain stable and maintain its position throughout the entire survey, which may last a few minutes [16]. During the drone operation, attention must be given to weather conditions, especially wind, as it can adversely impact drone performance [43]. At the end of this phase, all collected inspection data is stored for post-processing.

The Post-Inspection Phase includes everything that occurs after the Main Inspection Phase. For the sake of generating a high-quality 3D model of the structure through photogrammetry, the acquired images and data are processed for visualization, damage assessment, or modal analysis. As far as damage detection is concerned, it is necessary to assess first the quality of the images [45]. Several commercial software packages such as Agisoft Photoscan and Pix4Dmapper, as well as open-source projects like COLMAP and WebODM, are available for 3D structure reconstruction [45]. The next step is to identify damages including localization, classification, and quantification [36]. To expedite the time required for damage detection, training a deep learning algorithm and artificial intelligence can assist in managing and processing the huge amount of collected image data and identifying defects [47]. On the other hand, as far as modal analysis is concerned, the acquired videos are post-processed using specialized algorithms, which identify and track the displacement time series of the measured points on the bridge. Some of these algorithms include Kanade-Lucas-Tomasi (KLT) [48] and Digital Image Correlation (DIC) [49]. It is possible to compensate for the drone's oscillations by using stabilization methods such as fixed-point tracking [29], inertial compensation [50], or high-pass filtering [30,35]. Once the displacement time series are obtained, classical Operational Modal Analysis (OMA) techniques can be applied to extract frequencies and modal shapes [30,51].

Eventually, when damage is identified on bridges, an in-depth condition assessment of structural members is conducted [12].

3.2. Path planning and optimization

Given the limited flight durations of drones, optimizing data collection is essential. This optimization involves (i) identifying Points Of Interest (POI) where sensor readings are necessary, and (ii) planning an efficient traversal route for the drone to minimize overall flight time while maximizing battery life.

When planning the flight path of the drone, several key criteria must be addressed: ensuring collision-free flight, achieving full coverage of the structure, obtaining images of sufficient quality for 3D reconstruction and feature detection, minimizing the number of images, and devising efficient flight routes [43]. Additionally, depending on the purpose of the monitoring, it is important to consider the distance between the drone and the target, the optimal flight speed for achieving good resolution, the percentage of image overlap, and the timing of the flight, intended as the assessment of the optimal environmental condition along the day [24]. The analysis of the existing literature reveals several approaches to addressing flight path optimization and related aspects.

For flight path optimization, a common solution involves flying the drone in vertical or horizontal strips, following a zig-zag pattern across the area of interest while avoiding obstacles [24]. This method is frequently referred to as "the strip method" and has been tested by [39], which compared the differences between using vertical and horizontal strips. They determined that horizontal strips are more effective, particularly when combined with a low flight speed. Instead, Steffen & Forstner [52] present research that supports the use of Archimedean spirals to optimize flight plans.

Smaoui et al. [53] focus on optimizing Coverage Path Planning (CPP) for drones, proposing a back-and-forth method to ensure comprehensive image coverage of the Region Of Interest (ROI) while minimizing time and energy consumption. Effective autonomous mission management relies on data streams from positioning systems like GNSS. In contrast, Morgenthal et al. [43] present a method for generating flight paths aimed at automatic image acquisition to facilitate photogrammetric 3D reconstruction. Utilizing software such as Pix4D Capture, they create virtual models of structures based on initial drone surveys or existing data. Viewpoints are identified within a surface offset surrounding the virtual structure, and an optimal path connecting these viewpoints is determined using the Lin-Kernighan-Helsgaun (LKH) solver algorithm, enabling autonomous operation through onboard navigation systems. An example of the generated path is shown in Fig. 4. Bolognini et al. [35] propose a system that separates the identification of POIs and the creation of efficient drone trajectories. They pinpoint POI positions based on a detailed mesh model of a building, cluster them for simplified trajectory planning, and solve a Capacitated Vehicle Routing Problem (CVRP) to ensure efficient navigation, considering battery constraints. Zhao et al. [54] use a genetic algorithm to optimize the path, with the constraint of full coverage of the bridge.

Another important factor is the optimal distance between the drone and the target. Depending on the type and purpose of the monitoring, the drone can operate at various distances [10]. For example, thermal imaging is characterized by the decrease in the measured temperature of an object as the distance between the camera and the target increases. Distances from 30 m to 10 m are typically encountered in the case of scanning and reconstructing a 3D model of the entire structure [13,55]. Smaller distances are needed for damage detection. For instance, Morgenthal et al. [43] used a constant viewing distance of 4.50 m leading to a mean object resolution of 0.6 mm/pixel and a spatial accuracy of ±1.70 mm. Duque et al. [44] demonstrated that by using a high-resolution camera, it is possible to detect a crack with a thickness of 0.75 mm from a distance of 3.00 m [40]. Smaller distances are required for monitoring displacements, and frequencies, and conducting modal analysis.

Table 4 presents a compilation of case studies from the literature, detailing the distances maintained between the drone and the target for various inspection purposes. The distance is also influenced by lighting conditions, as demonstrated by Dorafshan et al. [56], which quantified the maximum crack-to-camera distance for identifying fatigue cracks on steel specimens as 0.30 m under poor lighting conditions and up to 1.10 m under good lighting conditions. Additionally, a safety distance must be considered to avoid obstacles and comply with restrictions imposed by authorities. For instance, the Federal Railroad Administration requires a safe distance of 4.60 m from railroad bridges [29].

Optimal flight speed is a crucial factor. The drone needs to maintain a balance, flying fast enough for battery saving yet slow enough to ensure high-quality image collection. Three main factors must be considered when using a drone for capturing images. First, the interval between consecutive images is crucial; the drone speed must be aligned with the camera's capability to capture images at specified intervals. This interval is influenced by the required overlap between images, which should range from 60 % to 90 %, according to various studies [24]. Second, the camera's photo interval, which is the time required to save captured images, plays a significant role. During this period, the camera cannot take additional pictures, so flying the drone too quickly could result in the loss of important data. Lastly, exposure time is a critical factor, particularly for daytime photography, where short exposure times are common. The camera's shutter speed is affected by daylight settings, and any movement during an open shutter can result in blurred images due to the larger area of light captured.

The timing of the flight is another crucial factor to be considered. Shadow occlusion, daylight, and solar radiation can cause overexposure during image acquisition, affecting the emissivity of materials and resulting in false positives or exaggerated readings. González-Aguilera et al. [57] opted to take images before sunrise and after sunset to avoid false positives caused by direct radiation. Colantonio & McIntosh [58] recommend conducting exterior inspections at night to minimize the effects of solar heat gain on the building envelope cladding. Lizarazo et al. [59] performed test flights between 9:00 am and 11:00 am to ensure consistent solar illumination throughout the data collection period.

Another problem that can happen is the low battery levels [42]. In this case, the drone may be unable to complete the entire scheduled mission. This could occur due to unexpected drainage or insufficient charging before mission commencement. To safeguard the drone from potential damage, a failsafe mechanism activates when the battery voltage reaches a specific threshold. The battery level is continuously monitored during the mission, and if the threshold is reached, the drone

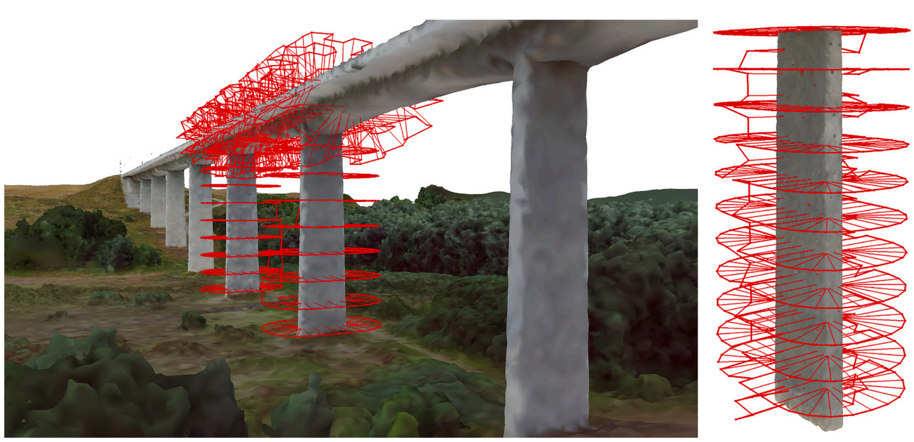

Fig. 4. Generated flight path for the inspection based on the rough 3D model [43].

initiates a return to its home point. In situations where the drone is too far from the starting point and the battery voltage is critically low for a safe return, it will promptly initiate a landing.

3.3. Challenges and research directions in inspection procedures

This section concludes by emphasizing the critical importance of the planning phase in bridge inspections. Effective planning encompasses not only path planning but also a comprehensive consideration of timing, environmental conditions, safety and regulatory requirements, the data to be acquired, and how they will be stored and delivered. To address these aspects effectively, three key considerations arise. Firstly, bridge inspectors should receive thorough multidisciplinary training that equips them with a robust understanding of bridge SHM, drone operation, and data management. Secondly, academic research, in collaboration with industry professionals, should focus on developing a more detailed framework and standardized guidelines. Thirdly, academic research may focus on more complete flight planning algorithms, to optimize data gathering and battery consumption. Such efforts would streamline procedures and outputs, ensuring high-quality, objective, and consistent inspections. These measures are essential for improving the reliability and effectiveness of drone-based bridge inspections and contributing to better infrastructure management.

4. Communication technology

Data collected by drones must be transmitted to allow their use for decision support. When networks of drones are involved in bridge network monitoring, the Internet of Drones (IoD) environment can greatly enhance their performance. The goal of this section is to provide insight into the IoD environment, that is conceived as a network architecture that connects drones and a number of network entities deployed on the ground. The IoD has attracted much interest in the recent literature, due to the flexibility and adaptability of networks of drones in a wide variety of scenarios, and their ability to enhance the performance of other network architectures, in terms of network connectivity, load distribution and data losses.

4.1. Internet of drones

The diffusion and interconnection of drones made necessary the standardization of communication within networks of drones. The so-called IoD is a network architecture to support communications between drones and Ground Control Station (GCS) [8] and coordinate access to controlled airspace [108]. Fig. 5 shows the structure of IoD and the standards for drone interoperability which include communication protocols, flight procedures in controlled airspace, and resource management, in terms of energy and bandwidth consumption.

Within the IoD, drones are considered intelligent objects capable of communication among themselves and with the GCS, to exchange mission-related data [8,60]. In turn, GCS constitutes the hardware for remote control. It supervises the airspace and monitors the drones' mutual positions. Typically, the GCS has a high processing capacity, as it is responsible for the management of the information received from the drone and its transmission to end users, without impacting the drone's limited resources [8,61].

Critical issues in the IoD environment include: (i) Inter-drone conflicts; (ii) Flight duration; (iii) Communication channel; (iv) Routing protocols; and (v) Security issues in drone communication.

Inter-drone conflicts. In multi-drone systems, also called swarms of drones, drones cooperate to complete one or more missions. The number of drones involved can vary from two to hundreds of units, depending on the task they have to perform. In case of conflict, drones can selectively change their route to optimize energy consumption.

Flight duration. The battery life of a drone represents a limitation in missions taking place over very large areas. This problem is also present in the world of the IoT. Some solutions proposed in the literature for increasing the autonomy of a drone include: efficient battery management [62,63]; implementation of wireless charging stations, battery replacement, or drone maintenance [64]; introduction of solar panels on the wing surface of the drone; adoption of Machine Learning (ML) and communication techniques.

Communication channel. The medium used by drones for communication is wireless. The advantages of this kind of channel include a high degree of mobility and cost reduction, if compared to wired networks. Nevertheless, the wireless medium presents some intrinsic problems, mainly related to the unreliability of the medium and the presence of multiple paths and attenuations due to physical obstacles (trees, mountains, buildings, etc.) [8]. An IoD communication should meet the following requirements [65]: Efficient data link; long-range operation, two-way communication, low latency, high flight autonomy, and communication reliability. To avoid interferences, the most relevant transmission techniques are widely used in the 2.4 GHz band [65,66].

Routing protocols. Routing protocols are protocols at the network layer which are responsible for establishing the optimal path for packet routing. The main routing protocols used in drone networks are based on protocols already existing for Mobile Ad-hoc networks NETworks

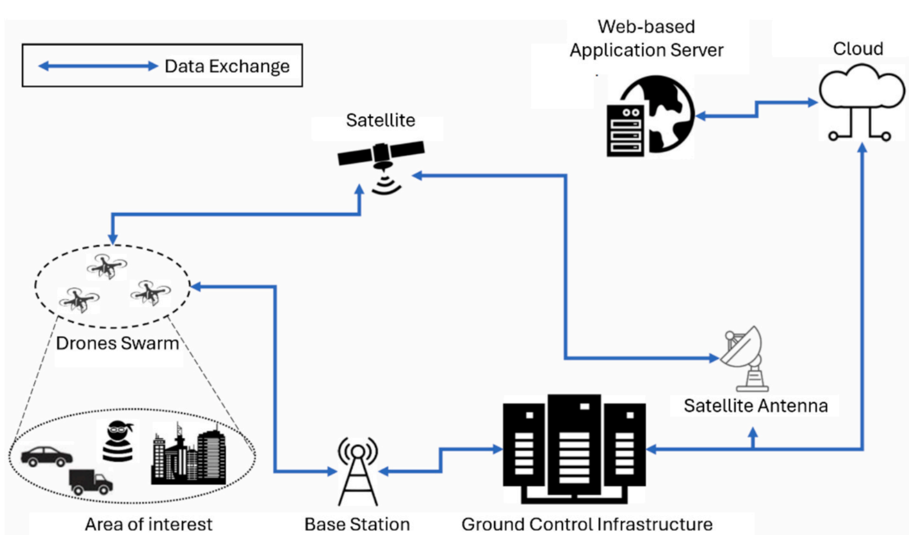

Fig. 5. Reference IoD architecture.

(MANET) [67].

The metrics used for path comparison are end-to-end delay, total traffic received, data loss and throughput. It is not possible to establish a routing protocol universally suitable for the networks of drones since the protocol's effectiveness varies based on the number of nodes and the speed of the drones [67]. Some of the routing protocols can be improved by increasing their performance in terms of packet delivery rate and end-to-end delay [68]. However, they can present problems of adaptability to frequent variations in the drone's formation.

Security issues in drone communication. Security protocols used on drones must be lightweight, due to the limited resources. However, common encryption solutions usually require high computational capabilities and, consequently, a considerable use of resources.

To demonstrate the vulnerability of drones to cyber-attacks, several tests have been conducted on drone prototypes [69]. Results show that all the attacks achieved a success rate between 48 % and 64 %, thus highlighting the importance of implementing more efficient security protocols. Secret keys can be used to guarantee the confidentiality of data sent from the drone to the ground station, also achieving performance gains in terms of throughput [70,71]. Also, blockchain can allow secure communication, with low demands in terms of computational capabilities. Blockchain-based schemes have been analyzed to create a decentralized registry.

4.2. Technologies and protocols for the IoD

The selection of the wireless technology used for drone communication at the physical layer is of great importance to optimize the communication performance of networks of drones. It depends on many factors, including the type of drone tasks, their duration, the environment, drone mobility, communication range, limitations on transmitted data or energy consumption. For example, technologies like cellular networks and satellite communications can cover large areas, providing high throughput and reliable connectivity; nevertheless, they require high energy consumption and delay. Vice versa, technologies like Bluetooth and Zigbee have an extremely low power footprint and delay, but also a low transmission bandwidth, and throughput, and are more subject to interferences caused by obstacles [8].

Given all these premises, in what follows the most relevant technologies for IoD communication are synthetically discussed.

Wi-Fi communication. The widely known Wi-Fi radio channels in the 2.4 GHz and 5.8 GHz bands are also used to control drones via Radio Control (RC) devices like smartphones and tablets [72]. Using the Wi-Fi band has the advantage of transmitting data and images in real-time at high speed [72]. However, the transmission of flight commands over the Wi-Fi band is subject to interferences, since it occurs in the unlicensed Industrial, Scientific and Medical (ISM) band which is used by many devices [73]. To this end, RC systems that operate on frequency bands different from those of Wi-Fi can be a valid option [74].

mmWave communication. The mmWave technology is particularly attractive in the IoD, because of its intrinsic advantages in terms of very high frequency and increased bandwidth, and beam-forming due to the short wavelength. Nevertheless, there are also disadvantages of translating into attenuation in free space propagation and blocking effect due to obstacles and objects.

Different aspects related to the mmWave technology are investigated in modern research, ranging from channel propagation characteristics to the implementation of beam-forming techniques that account for channel variations, the impact of the Doppler effect due to drone mobility, and the adoption of spatial-division multiple access to increase the network capacity [8]. This technology is not only typical of access networks; it can also be employed for backhaul links in drone-assisted networks, where drones act as relay nodes. This technology can also be integrated with the last-generation cellular networks (5G, or 5GB) to provide reliable connectivity among drones and in the backhaul link [75]. Also, the Air-to-Ground (A2G) channel can exploit the mmWave data transmission for drone communications, in different mmWave frequency bands and several environments (urban, suburban, rural, and overseas).

The mmWave communication suffers from some important issues that need to be properly addressed to provide reliable connectivity [76,77]. That is, a LoS path is required between a drone and a ground station, or another drone, to reach a high-rate, low-latency transmission. In case of obstacles of whatever nature (buildings, vegetation, differences in the ground height, etc.) can disrupt the LoS channel, degrading the mmWave communication performance. Accordingly, drone communication through mmWave technology can be an attractive solution only for some specific scenarios, like high-quality multimedia transmission in LoS coverage. An alternative solution to provide mmWave connectivity for swarms of drones is the implementation of 3D antenna arrays, whose aim is the implementation of Multiple Input Multiple Output (MIMO) techniques to perform beamforming [76,78].

Machine-type communication. Machine-Type Communication (MTC) can be used in drone networks and application scenarios like public safety. Two kinds of MTC communications can be considered, whether the communication range is short or wide. Wide-range communications provide coverage over a large area. In this category fall cellular communication, WiMAX, and satellite communication. On the contrary, short-range communication is used for small-area coverage. In this second category fall, among others, Zigbee and Bluetooth. Wide-range communication technologies are suitable for the control of drones flying at high altitudes and from long distances. In this scenario, also last-generation cellular networks are particularly attractive to guarantee reliable drone connectivity for data collection and processing, as well as for video streaming applications [14,77].

Cellular technology. Drones need to be controlled beyond the LoS in several application scenarios. This task can be accomplished thanks to the integration with cellular networks, where each cell is managed by the Base Station (BS) that provides radio coverage over a defined area, also guaranteeing persistent connectivity to the User Equipments (UEs). Accordingly, multiple BSs greatly increase the total coverage area and provide connection redundancy and capacity increase [14]. Cellular networks can overcome the problem of limited bandwidth and coverage when the ISM band is used, due to the cellular network's ability to provide wide coverage with high throughput, and with low-power small devices which characterize drones' connectivity hardware. As regards video streaming, 4G networks can improve throughput, loss rate and delay if used in combination with drones, despite the negative aspects of multipath propagation, shadowing, and fading that characterize the wireless channel. A high video encoding efficiency is beneficial for seamless video transmission. In this context, a network architecture consisting of indoor femtocells and outdoor macro-cells is particularly efficient [14].

In recent years, the rapid growth of 5G-and-Beyond (5GB) cellular networks has paved the way for several applications and technologies involving drones [75]. Specifically, drone swarms can rely on 5GB networks to transmit huge amounts of data, like high-quality videos and images, in surveillance and monitoring scenarios [79,80]. Drones can efficiently be used as BSs to deliver wireless connectivity in areas where the ground cellular infrastructure is poor or absent, like rural areas, or can serve to provide temporary coverage for limited-time events, abating the costs of network deployment [14]. Drones used as BSs have also the capability to relay data to other networks, offloading the terrestrial network, saving resource consumption and reducing interferences with adjacent cells [79,81,82]. *Fig. 6* depicts a schematic representation of a drone-assisted 5GB cellular network [73,75].

The current cellular wireless networks integrating drones exploit different technologies to reach this goal, like D2D communications, small-cell networks and mmWave communications [73].

WiMAX technology. WiMAX is an enabling technology to provide broadband access over relatively large areas. If compared to the more widespread WiFi, it covers larger distances at a lower cost, reaching a

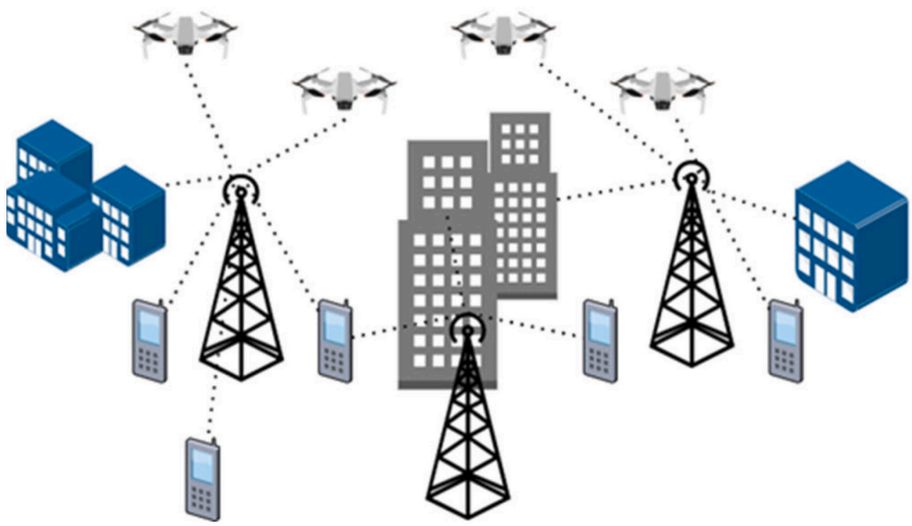

Fig. 6. Drone-assisted 5GB cellular network [75].

theoretical data rate of about 75 Mb/s per user for the fixed part of the network, and 30 Mb/s for the mobile part of it [84]. The WiMAX technology can be used in some application scenarios involving networks of drones, like rescue systems and emergencies, where drones can communicate through WiMAX because of its peculiarities, i.e., support for mesh networks, capability of differentiating different traffic types, support of security (authentication and encryption), throughput and coverage capabilities, support for mobility, low cost and ease of installation. According to several studies, WiMAX can also be used for command and control of drones due to its low Round Trip Time (RTT) and jitter [14].

As testified in [14], the peculiarity of mobile WiMAX to define different Quality of Service (QoS) classes corresponding to different requirements for data rate and delay makes it suitable for applications for transmission of control information of fleets of drones, like, for example, flight routes and telemetry, and under different environmental circumstances.

Satellite communication technology. There are situations where the drone is not in the visibility range to transmit data to other drones, or the ground station. In this case, satellite communications (SATCOM) can be of great help in guaranteeing communication. Moreover, SATCOM is of paramount importance to guarantee mission-critical communications. SATCOM can be used in different scenarios: for drone communication or as a relay for A2G communication [14]. Furthermore, because of the high channel capacity of the satellite link, SATCOM can be used for multimedia data transmission, like live photos and videos through drones, even if the end-to-end delay increases if compared to ground network scenarios. As regards satellites used as relay nodes, the transmission performance depends on several factors like drones' transmission power, data rate and satellite transmission power. This solution can be considered as a valid alternative to networks of drones in which the latter are used as relay nodes, because of the larger overlay range and the higher stability and data rate of the satellite link. This holds especially in applications that require transmission of high volumes of data, like transmission of high-quality images over long distances [14].

Bluetooth technology. Bluetooth (IEEE 802.15.1) is a standardized short-range protocol, with a maximum range of 100 m, aiming at a low power consumption. There are three versions of this technology, that differ for the operating data rate. The maximum data rate is instead of 24 Mbps [82,83]. This technology can be adopted also for flying networks of drones, but preferably integrated with other wireless communication technologies, due to the short-range communication [14]. Bluetooth can be applied to drone-based platforms with short-range communication to support distributed sensing and control operations, where the drone flights autonomously and carries on different missions with low computational power and reliable communication [86]. Studies on this technology applied to drones have testified that different real-world implementations, like drone collision avoidance, obstacle avoidance, formation flight for task accomplishment, etc., are possible [14].

Zigbee technology. Zigbee (IEEE 802.15.4) is a low-power standardized protocol suite, that also includes security aspects, used for low data rate communications where energy saving is a particularly stringent requirement. If used in mesh network configurations, it reaches also larger coverage ranges. At the physical layer, it presents an increased signal robustness against interference. Data rates are relatively low, reaching up to 250 kbps at the frequency of 2.4 GHz. Zigbee is used mainly for intermittent data transmission in Internet of Things (IoT) scenarios involving sensors, even if its application scenarios extend to control and monitoring applications, and home and factory automation [,85].

Applications of ZigBee in networks of drones are limited to indoor environments for drone localization purposes, preferably in combination with other inertial systems to increase position accuracy [88], or for communication and position estimation during the drone landing phase [85].

Other communication technologies. Cognitive Radio (CR) technology is a promising solution to mitigate the main issues in spectrum utilization of other wireless technologies (Wi-Fi, Bluetooth, or cellular communications) for drone-based applications. CR technology allows for accessing the spectrum in an opportunistic way, by sensing it through advanced radio techniques and transmitting data over bands that are not utilized by other transmissions [87]. It also allows the simultaneous use of the same spectrum to serve different users, without exceeding an interference threshold. Optical wireless communication has been studied in recent works for the so-called Free Space Optical (FSO) communication systems. The latter exploits the optical signal for high data rate communications over relatively long distances. In FSO systems, drones can act as relays moving in the space [88,89].

In networks of drones, the Long-Term Evolution -Unlicensed (LTE-U) technology can be used for communication among drones that act as BSs, to increase throughput by exploiting the unlicensed spectrum. In critical scenarios, drone-BSs make use of LTE-U to fill coverage gaps due to, for example, damaged infrastructures that adopt other wireless technologies [90,91].

Table 2 provides a synthesis of the most relevant communication technologies for the IoD, with related data transmission requirements, communication ranges, and main advantages and disadvantages.

Table 2
Comparison of communication technologies for IoD.

Communication Technology	Data rate	Communication range	Advantages	Disadvantages
WiFi	Up to 100 Gbps	About 100 m (outdoor)	High transmission rate Real-time data transmission	High signal interferences
mmWave	Up to 7 Gbps	From 20 m (omnidirectional) to 100 m (directional) in LoS	Very high frequency and transmission rate	High signal attenuation and interferences LoS coverage
Cellular (LTE, 5G)	Up to 20 Gbps	Several km	Large coverage area High data rate	Multipath propagation, shadowing and fading effects
WiMAX	Up to 75 Mbps	Up to 50 km (LoS)	High-speed transmission over long distances Large coverage area Low cost	Signal interferences LoS channel for long distances
SATCOM	About 20 Gbps	Hundreds of square km	Beyond LOS (BLOS) communications High data rate Large coverage areas Support for mission-critical communications	High transmission delay High transmission power High costs of implementation and maintenance
Bluetooth	Up to 2 Mbps	Up to 100 m	Low power consumption Low interference High compatibility	Low data rate Low transmission range Security vulnerabilities
ZigBee	Up to 250 Kbps	Up to 100 m	Low-power transmission and high battery life Low-cost implementation	Low data rate Low transmission range

4.3. Application example for IoD: the urban scenario

Although not already fully exploited in bridge inspection, the IoD paradigm can be fruitfully exploited in urban environments, where data coming from different sources are collected and processed, often in real-time, for different purposes like traffic monitoring, detection of events, rescue of people, emergency management, and public safety [92]. The general framework considers a network of drones that acquire data coming from sensors placed onboard the drones and/or relay data coming from ground sensors. Sensors can be of different kinds, according to the specific quantity to be monitored (e.g., video or sound, air quality, temperature, pressure, noise) [92]. Due to the very limited amount of processing resources of the drones, all the collected data are transferred and processed to purpose-specific servers, that can be placed at the edge of the network (i.e., a peripheral part of the network) or in the Cloud. Drones can accomplish different kinds of tasks, depending on the specific application implemented in the urban context. For example, one of the most important applications of IoD in urban scenarios is the real-time monitoring of different aspects of urban life like air quality, noise pollution and rubbish detection. IoD can also be adopted for traffic improvement. In fact, sensors distributed throughout the city and/or onboard the drones can provide useful traffic information, like congestion degree in specific city areas, the detection of accidents, or the check of road conditions. A network made of drones can assist other networks in disaster scenarios, big events (like sport events, concerts, etc.) and IoT applications [92].

Since the urban environment is full of obstacles and reflective surfaces that degrade and distort the signal, communication technology plays an important role to guarantee reliable and low-latency data transfer. This explains why part of research efforts in the IoD are devoted to developing data routing and position optimization algorithms to reduce signal reflections and attenuations [93]. Moreover, the optimal routes computed by sophisticated routing and path planning algorithms aim to minimize the energy consumption of the drones [94].

To deliver data from sensors to the network Edge/Cloud, the IoD network is integrated with other networks such as vehicular networks, cellular networks, and IoT networks. Such integration is exploited to connect vehicles, reducing latencies and data losses when broadcasting information on natural disasters, critical weather conditions and accidents. Air quality monitoring makes extensive use of IoT devices, that often have a limited transmission capacity. Accordingly, drones are used to increase the transmission range and coverage [92]. In this context, a concrete possibility is that drones first reach the location of IoT devices to gather data and then deliver data to the ground station for post-processing and analysis. Once again, path planning algorithms play a critical role for the same reasons highlighted above.

Drones can collect and deliver heterogeneous data, of whatever kind (images, videos, drone position and velocity, sensed measurements, etc.) and some of them can be sensitive and/or life-threatening, making security and privacy a critical issue [94]. There is not any standardized scheme to implement such features in IoD. The solution followed is to implement cryptographic mechanisms and authentication schemes borrowed by the classical Internet scenarios. Nevertheless, all the security algorithms have not been conceived for resource-constrained devices like drones. This implies that more investigation is needed to reduce the computational complexity of cryptographic and authentication mechanisms, at the same time keeping a high level of robustness against attacks and security breaches. Also privacy should be guaranteed, making drones more “privacy-oriented”; a concrete possibility is the adoption of machine learning techniques that can be implemented both in the IoD and IoT networks [94].

As a result of those successful application examples, author expect that IoD will make data management and transmission cheaper and safer for bridge inspections in complex environments. A deeper discussion of research trends in presented in Section 4.4.

4.4. Challenges and research directions in the IoD

The IoD is a fascinating topic, due to its adaptability to a wide variety of application scenarios, its flexibility in network formation and configuration, its integration with terrestrial networks for data exchange, and the capability of drones to act and coordinate autonomously, or with very limited intervention by humans. At the physical layer, the analysis of the recent literature on this topic confirms that different technologies can be used for communication among drones and between drones and the ground infrastructure. The most suitable of them are chosen to meet different needs, from the increase the coverage performance to the allocation of channel resources and the improvement of path reliability and planning, and position optimization. The most relevant challenges in this aspect are mainly connected to real-world operating conditions, such as NLoS conditions and/or the presence of obstacles. To face these issues, the choice of the most suitable communication technology that matches the specific application needs is a viable solution, which depends on several factors, i.e., the environment, the communication range among drones and between drones and terrestrial nodes, and energy consumption [8]. In addition, connectivity can be improved through modulation techniques specifically employed for drone-based networks, and the development of accurate channel models to study coverage performance, resource allocation and reliability in data routing, path planning and position optimization of drones. Research in this context is moving on to the implementation of optimization algorithms for resource allocation and path planning, which are very important topics in the IoD framework. Specifically, the recent research focuses on i) path planning algorithms that consider energy consumption and safety, ii) mathematical models for path planning optimization, iii) route planning in smart cities, and iv) simulation tools of real IoD applications [95,96]. The main challenges are that the drone path planning algorithms must run in real-time, requiring high computational load and energy consumption to find the optimal solution. This is a serious drawback for drones, that are battery-powered and with limited computational resources. Other challenges are related to the practical integration between drones and terrestrial nodes, especially in monitoring and controlling IoD applications, and the development of accurate tools considering multi-drone interactions [95].

Another critical aspect is the IoD integration with terrestrial networks. In this context, research efforts have been directed towards the design and implementation of innovative networks, able to integrate swarms of drones with other terrestrial network infrastructures like Vehicular Ad-hoc NETworks (VANETs), Public Transportation Systems (PTNs), cellular networks, or IoT networks. As obvious, the integration must be "intelligent", that is, it must take into account the different characteristics of each network, demanding to the IoD network the critical task of bridging the terrestrial networks, and taking into account the network features in terms of connectivity, energy consumption, network resiliency and application scenarios [93]. The challenges to be faced in this field can be summarized into: i) the management of heterogeneous data to avoid unnecessary data overload due to the lack of synchronization among networks, ii) the integration of networks with different energy and capacity bounds, iii) the implementation of ad-hoc routing protocols that consider the integration of IoD with other heterogeneous networks, iv) the optimization of existing applications, in terms of reliability, and the creation of new ones that can benefit from the network integration, and v) the secure cooperation and interoperability among different networks, that must guarantee privacy and security in the plurality of applications and services [93]. To this end, research is focusing on the development of a cooperative schema to increase communication efficiency and reduce data overhead and losses, together with scheduling mechanisms to decide which node must transmit the information, when, and at what frequency. This in turn implies the adoption of efficient synchronization mechanisms among drones and different networks [8].

Energy efficiency is of paramount importance in the IoD and is one of the most analyzed aspects of recent research. In the vast majority of IoD applications, drones are employed to acquire and exchange data that will be subject to processing. Nevertheless, data processing cannot be performed onboard the drones because of their limited amount of computational resources, but it should be demanded by centralized systems with high capacity, in terms of both processing units and amount of memory. The main goal, in this context, is the offloading capacity of drones to optimize metrics like the power consumption of the drones, the ground network and the processing centers, and the distance travelled by the drone to offload data. Solutions have been proposed in literature, that exploit Fog computing jointly acting with the Cloud servers to meet these requirements [97]. From the research studies it emerges that several factors influence energy efficiency: drone speed, trajectories and path, deployment of relay nodes of terrestrial networks, the choice of communication technology (as described in Section 4.2), resource allocation, scheduling of data transmission, cooperation among drones, and computational offloading. Nevertheless, the metrics to be optimized often require the solution of multi-objective algorithms, very complex to implement [95]. Another challenge resides in the very frequent changes in the drone network topology because of the high mobility of drones. This requires a very frequent update of the information of the drone state (e.g., their position and velocity), which in turn brings to an additional exchange of control information among drones and/or ground nodes [8].

The IoD has great potential to ease and automate operations in a wide variety of application scenarios. Nevertheless, sensitive data can very easily be exchanged through the wireless medium, which is open. This poses important security concerns, that are deeply analyzed in the current research on IoD. It is well known that drones usually collect and exchange data like videos, images and side information (e.g., GPS coordinates, date and time) as captured from the sensors onboard. This information is very often critical and should never be leaked or compromised in whatever situation. Security requirements, in terms of data confidentiality, integrity, availability and authenticity as well as privacy preservation, are critical for IoD. Recent research has made significant efforts to implement robust security mechanisms that can be managed with the limited resources of drones to tackle threats and security breaches [98]. The security solutions proposed in the recent literature on this topic include authentication mechanisms, intrusion detection and privacy preservation strategies. Authentication in IoD is reached through biometric approaches, hashing operations, cryptographic schemes, predictive methodologies, lightweight cryptosystems, Authentication Key Agreement (AKA) schemes, and the adoption of blockchain-based schemes. Intrusion detection schemes for the IoD consider the integration with neural networks and big data analytics. Privacy preservation is performed mainly through policy-based or technique-based mechanisms [94,98]. Some challenges need to be overcome for efficient security in IoD. The most relevant of them is that robust schemes and low computation and communication costs are both important, yet contrasting, requirements: lightweight schema can have security weaknesses, and robust schemes require high computational and transmission costs. So, the best trade-off between efficiency and low computational cost must be found. There is also a regulatory aspect that must be taken into account when drones are employed. Privacy concerns arise whenever data propagation occurs (i.e., whenever drones acquire images and/or videos with private information). The countermeasures taken (e.g., censoring information, or deleting the image/video) strongly depend on the regulatory laws nevertheless are not uniform for all countries and depend on "local" laws. To bridge this gap homogeneous, worldwide regulatory laws for IoD activities would be desirable, but this challenge will be very difficult to overcome in the next future [8,92].

5. Inspection outcomes for damage detection

This section presents two primary applications of drone-based inspections. The first focuses on using drone-mounted cameras for surface damage detection and on the integration of surface damage with Bridge Information Models (BrIM). The second examines drone-based techniques for SHM, focusing on dynamic characterization of bridges and on non-destructive testing.

5.1. Surface damage detection and 3D reconstruction

Drones provide bridge inspectors with quick and safe access to hard-to-reach areas, without the need for expensive equipment, and requiring relatively short data collection times. Inspection data can be directly used on site, as images are made available to the operator for an immediate and qualitative visual judgment of the bridge conditions. Moreover, data can be post-processed to obtain quantitative information on large datasets. For instance, the use of computer vision techniques enables the condition assessment of bridge elements using images gathered from the drone, evaluating the number and width of cracks starting from hundreds of images. Furthermore, drones can be used for the reconstruction of 3D point clouds that provide easily interpretable information regarding surface damage. Finally, the integration with BrIM is crucial for providing objective estimations of bridge degradation over time [13].

5.1.1. Automated surface damage detection

Automated surface damage detection exploits ML algorithms to recognize recurrent surface damage patterns. The input is usually a set of images that can be simply RGB (i.e. the one taken even by a smartphone camera), or coming from specialized cameras, as in the case of infrared thermography. The most recognized anomalies include cracks, exposed and oxidized reinforcement bars, superficial defects such as efflorescence, and vegetation. There is a wide range of studies, coming from the field of computer vision, that exploit a wide variety of algorithms to perform surface damage and, more specifically, crack detection. Cracks are a common type of surface damage. The possible output of crack detection includes crack number, length, and width. For example, Perry et al. [99] proposed an algorithm trained for the identification of common damages such as cracks and spalling. An OpenCV library is used: the colored image is corrected and transformed into a grey-scale image. Then, a canny edge detector is used to identify cracks. It is, therefore, possible to identify the number of cracks and their length, but not their opening width. Other papers pay attention to recognizing different damage types. For instance, Belcore et al. [100] present OBIA (object-oriented supervised ML) exploiting segmentation to group similar pixels into objects and then classification to organize objects into classes (e.g. areas with unwanted water drainage, oxidized rebars).

Finally, in both cases of crack detection and damage recognition, images can be pre-processed or post-processed to improve the quality of results. Duque et al. [44] distinguish high-quality to low-quality images, based on the definition of sharpness and entropy of a single image. Successively, images are processed either by using pixel-based measurement software (ImageJ) or by using a photogrammetric approach. Results are compared in terms of the quality of the result and computational time. Jeong et al. [101] propose a procedure in which, after damage detection with ML, the quality of images containing damages is improved to ease elaboration and measurements. Improvements regards contrast, brightness, and sharpness. Various types of damage, including split, crack, weathering timber, and paint failure are detected using a Convolutional Neural Network (CNN).

Some algorithms are specifically developed for low computational time, to enable real-time crack detection to guide the drone towards the most critical areas. Yang et al. [102] implemented a real-time damage detection algorithm integrated with drone flight, as illustrated in Fig. 7. The study highlights that relying on a ground server for real-time processing of drone-captured videos is not ideal for supporting real-time flight control. This approach can introduce delays due to video encoding, streaming, and potential interruptions in the video stream caused by connection issues, obstacles, or adverse weather conditions, which in turn increases response time. To address these challenges, the researchers suggest developing a lightweight, energy-efficient, real-time damage detection algorithm that can be deployed directly on drones, thus eliminating the need for extensive data exchange with external servers. S. Jiang et al. [103] implemented a real-time detection method based on the YOLO (You Only Look Once) family of neural networks,

Fig. 7. Examples of different types of annotated defect images in the concrete bridge damage dataset [104].

which is particularly suitable for high-speed and accurate object classification. Also, in this case, the drone has sufficient computational power to perform on-board damage detection. Drone guidance is aided by a vision-inertial fusion positioning method. The method is also provided with an automatic damage localization procedure.

Another way to perform surface damage detection is through the use of infrared images. Deteriorated areas on concrete (e.g. delamination areas) emit electromagnetic waves with slightly different intensity and wavelength distributions with respect to undamaged concrete. Based on the variation of those quantities, it is possible to classify surfaces of bridge portions according to their level of damage [105].

There is a wide range of approaches to extract information about surface damage from datasets. Each approach can be differentiated in terms of the methodology used and the type of output data, as indicated in Table 3. However, there are common issues that should be addressed, such as image quality, resolution and number of images, pre-processing and pre-selection of images, computational burden, requirements of pre-training, possibility of real-time use, quality of results, considering missed objects, false positives, dimensional estimations. Li et al. [106] remark interesting recommendations for effective image gathering, as follows.

- **Use high-resolution cameras**: Since crack identification relies significantly on image clarity, employing high-resolution cameras becomes crucial to improve the precision in crack size measurements. This holds for both manual measurements and image processing.
- **Provide adequate illumination**: Capturing images of cracks under low illumination conditions poses challenges due to reduced contrast. To mitigate these challenges and enhance accuracy, it is advisable to incorporate lighting equipment. Adequate illumination aids in overcoming difficulties and uncertainties associated with identifying crack edges.
- **Capturing from multiple orientations**: Crack edges situated in concrete erosion areas present unique challenges. Employing multiple images captured from diverse orientations can effectively diminish uncertainty in identifying edges and enhance precision in measurements.
- **Shortening the distance between the drone and the bridge**: Bringing the drone closer to the bridge during image capture can facilitate obtaining higher-resolution close-up images. To achieve this while ensuring safety, the use of safety equipment becomes essential. Shortening the distance between the drone and the bridge enhances the resolution of close-up images, contributing to more detailed and accurate crack assessments.

5.1.2. 3D point cloud and BrIM

3D point clouds are highly effective for supporting damage detection by providing inspectors with compact, photorealistic 3D models of bridges, where surface defects such as spalling and exposed rebars can be easily identified. Drones play a key role in creating these detailed 3D reconstructions through two primary methods: photogrammetric reconstruction and LiDAR scanning. Both approaches produce photorealistic 3D point clouds, which can be exported into Bridge Information Modeling (BrIM) systems to streamline bridge management and enhance data collection. When combined with automated crack detection or damage classification, these models significantly improve the efficiency of inspection processes. For instance, a database can be created to catalog cracks present in the bridge, detailing their size, location, and severity, which directly supports decision-making. A compelling application of 3D point clouds is their integration with virtual reality tools, allowing operators to conduct virtual inspections using a visor [4]. Achieving the highest resolution possible is crucial for detecting a maximum number of damaged elements. Regarding precision, Khaloo et al. [111] completed a 3D photogrammetric reconstruction of a trussed timber bridge, using images captured from a drone. The level of detail was sufficient to see details of joints and detect timber damage. The photogrammetric reconstruction outperformed the LIDAR-based reconstruction in terms of precision. However, even with high precision, detecting small cracks with opening widths in the millimeter range can be challenging. For instance, in the study by Mirzazade et al. [109], a 3D point cloud with sub-centimeter accuracy was generated, but it was insufficient to directly identify such fine cracks. To overcome this limitation, the point cloud was paired with a CNN designed to detect and segment cracks from 2D RGB images. In a subsequent step, the cracks identified in the 2D images were mapped onto the 3D point cloud to enable damage localization.

Another important aspect is bridge segmentation, which provides decision-makers with a clear understanding of which specific bridge components are damaged, as well as the extent and severity of the damage. H. Kim et al. [112] performed a semantic segmentation of bridge components (e.g., deck and piers) starting from a 3D cloud created from close-range images collected by a drone, as shown in Fig. 8. Perry et al. [99] successfully integrated damage detection with localization on a 3D point cloud, resulting in a Bridge BrIM enriched with detailed information on the number and characteristics of cracks for

Table 3
Comparison of methods employing drones for surface damage detection.

Reference	Research objective	Research method	Damage type	Research outcome
[99]	Crack detection and localization	Open-source crack detection algorithm + point cloud clustering for localization	Cracks	BIM model with damage information
[100]	Detection of different defects	Open-source software for segmentation and classification	Drainage, uncovered metal bar, oxidized rebar	Images with different damage types overlapped
[107]	Damage detection and quantification	Selection of high-quality images + pixel and photogrammetric-based methods to extract quantitative data (e.g. length, area)	Cracks, rust stain	Quantitative evaluation of crack length and width, and area of rust stain
[101]	Damage detection and classification	Improve image visibility + damage classification using CNN	Cracks, weathering, paint failure	Inspection report with cracks measurement
[103]	Real-time damage detection and localization	Lightweight CNN for + Simultaneous Localization And Mapping (SLAM) for damage localization	Cracks, spalling, corrosion	Bridge 2D image with information on damage
[105]	Damage identification through infrared thermography	Categorization of delamination severity using k-means clustering	Delamination	Condition map of bridge deck
[108]	Damage detection	DEEP (DEfect detection by Enhanced image Processing) software for pre-classification of structural elements and detection of defects	Paint absence, efflorescence corrosion, loss of thickness	Quantitative evaluation of defects
[109]	Crack localization, segmentation and overlapping on a 3D model	Hybrid approach: CNN for crack detection and segmentation + localization through photogrammetry	Cracks	Generated orthophoto as a photorealistic representation of detected crack with its measurement
[110]	Damage detection	Hybrid learning framework for damage detection and quantification	Rust area	Numerical evaluation of rust area

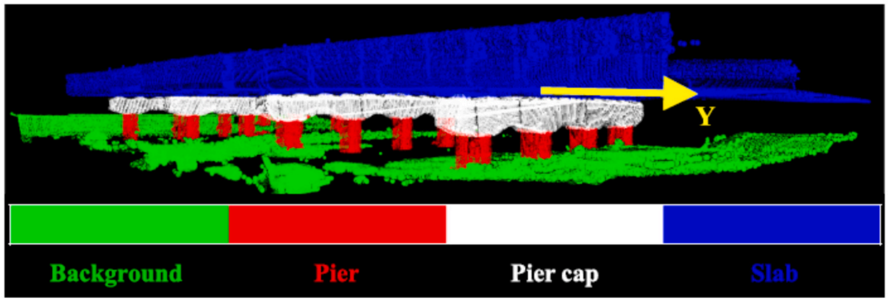

Fig. 8. BrIM with Semantic segmentation. From [63].

each bridge component. In the BrIM, “damage cubes” are placed at the damaged locations on the components, effectively documenting and visualizing component-specific damage information.

Additional studies [13,36] highlight the effectiveness of photogrammetric 3D point clouds for structural analysis. These studies demonstrate that high-quality 3D point clouds can be efficiently generated from partially overlapping RGB images of bridges, captured using standard cameras mounted on commercial drones. This method showcases how advanced 3D reconstructions can be achieved with widely accessible and cost-effective equipment. The on-site inspection process for a standard bridge typically takes around 1 to 4 h. Subsequently, photogrammetric software requires approximately 10 to 20 h of computational time to extract the 3D point cloud. The resulting 3D point cloud files are usually between 1 and 10 GB in size. Additionally, 2D orthomosaics can be derived from these 3D point clouds, significantly reducing storage requirements while retaining valuable structural details for analysis.

Perez Jimeno et al. [45] present an insightful comparison between traditional and drone-assisted inspection techniques. Their findings reveal that traditional inspection methods require approximately 240 min of fieldwork and three days of office work, relying on tools such as cameras, measuring tapes, flashlights, and computers. In contrast, drone-aided inspections significantly reduce fieldwork to just 60 min, though they require slightly more office work, totaling four days, using drones, GNSS, and computers. Notably, traditional methods provide access to only 80 % of the bridge, while drones enable comprehensive access to 100 % of the structure. Drone inspections also demonstrate higher accuracy in detecting damage, particularly in hard-to-reach areas. The study further suggests that integrating AI could streamline repetitive tasks and significantly reduce office time, while employing advanced hardware could enhance computational efficiency and overall performance.

5.2. Drones for structural monitoring

OMA techniques are used to determine the dynamic characteristics of a structure based on its response to operational loads or ambient excitation. These techniques can operate in either the frequency or time domain and aim to identify dynamic properties such as modal shapes, natural frequencies, and damping parameters. The identified modal parameters can serve various purposes. When developing a Finite Element model of a structure, parameters such as elastic modulus or cable prestressing force can be adjusted to align the model with the dynamic behavior observed in the real structure. Furthermore, conducting OMA throughout the structure’s lifespan, in conjunction with damage identification algorithms, provides insights into the structure’s health. For instance, changes in natural frequencies—whether gradual or abrupt—can indicate potential damage (e.g., stiffness reduction), reflecting alterations in the structural response.

The use of drones offers promising solutions for OMA, with two primary implementation approaches. The first, referred to as contact-based OMA involves the use of the drone as a mobile accelerometer. The second, known as vision-based OMA, employs a drone equipped with a camera to track bridge displacements, from which modal information can be derived. While precision-related challenges remain an important area for discussion, both methods share a significant advantage: they enable access to all bridge locations, including intrados and pillars, without posing any risk to the operator.

5.2.1. Drones for contact-based operational modal analysis

In the context of contact-based OMA, drones can act as mobile accelerometers by flying to and attaching themselves to different parts of a bridge. Each drone is equipped with an Inertial Measuring Unit (IMU) that includes embedded accelerometers, enabling even low-cost drones to conduct accelerometric measurements through direct contact. There are two primary methods for establishing contact between the drone and the bridge:

- The drone can land on the bridge, and measurement is performed when the drone propulsion system is turned off [113].
- The drone can hover in contact with the bridge intrados, with the propulsion system turned on. The so-called ceiling effect reduces the required thrust and ensures stable contact, as shown in Fig. 9 [114].

Both solutions for contact-based OMA necessitate careful consideration of the dynamic influence of the drone structure on the recorded frequency content. Factors such as the contact areas, suspension system, and damping characteristics must be analyzed to ensure accurate measurements. Additionally, when the drone is hovering, the blade rotation can introduce an extra dynamic effect, potentially impacting the recorded data. Measurement via direct landing is relatively straightforward in terms of data acquisition but may involve challenges such as partial traffic restrictions and complexities related to regulatory compliance, particularly in areas with strict drone operation rules. On the other hand, measurements taken while in contact with the intrados avoid interference with bridge traffic, offering a significant advantage in terms of operational feasibility.

Despite its potential, the application of contact-based modal analysis remains only partially explored in the literature, suggesting a need for further research to refine these methods and address the associated challenges.

To ensure proper contact during contact-based OMA, Sanchez-Cuevas et al. [114,115] exploit the so-called ceiling effect, a phenomenon where the airflow generated by the drone’s rotors creates a stabilizing force when the drone is close to the bridge surface. To ensure stable contact between the drone and the bridge intrados, a 3D-printed fairing is attached to the drone. Operating drones beneath bridges presents several challenges. One significant issue is the lack of GNSS signal, which renders traditional positioning and navigation methods ineffective in such environments. Additionally, the steel rebars within the bridge structure can interfere with the drone’s magnetometer, leading to imprecise altitude estimation. To address these challenges, techniques such as optical flow or visual odometry can be employed for navigation, providing reliable positioning in the absence of GNSS. In the

Fig. 9. Drone hovering attached to bridge intrados [114].

experiment, the drone is also equipped with a reflecting prism, enabling precise tracking through a total station, ensuring accurate navigation and positioning despite these constraints.

Mohammed et al. [113] investigate various contact-based approaches for drones used in acceleration tracking to assess vehicle weights on bridges. Their study introduces a perching system mechanism that employs double-sided re-stickable tabs or magnetic solenoids to establish mechanical surface contact. A drone equipped with these tabs was successfully affixed to a clean wooden bridge surface, and accelerometric measurements from the drone-mounted sensors were compared with those from a fixed accelerometer. The results showed a concordance in the first natural frequency at 14.57 Hz and a general alignment in the higher frequency spectrum, demonstrating the feasibility of contact-based modal analysis with drones.

However, several questions remain unanswered regarding the long-term reliability and precision of these methods [113]. For instance, the contact pads used in the study can only be employed twice before needing replacement, and their application on rough concrete surfaces may present challenges. Additionally, while the experiment was conducted with the drone's propulsion system turned off, performing measurements with the propulsion system active might introduce noise due to the ceiling effect, potentially impacting data accuracy. Furthermore, the performance of drone-mounted IMUs should be systematically compared with that of conventional accelerometers typically used in SHM for robust validation.

In another work, Mohammed et al. [116] describe a bridge inspection procedure utilizing a swarm of drones for both contact-based monitoring and visual crack detection. In this approach, contact is achieved through a small lift-suction solenoid electromagnet capable of holding up to 0.5 kg. While this mechanism shows potential, it has only been tested on traffic light columns.

To the authors' knowledge, no other studies have directly addressed contact-based bridge modal analysis. The coupling effect between the drone and the bridge structure remains an open area of research, particularly regarding its influence on measured frequencies. An example of the use of autonomous vehicles supporting moving accelerometers can be found in [117]. Another correlated research field involves the use of drones as manipulators to deploy and retrieve sensors that, once in contact with the bridge, are detached from the drone and therefore act as traditional accelerometers. [118,119]. In this case, the increase in accuracy of fixed accelerometric measurement is counterbalanced by the complexity of the deployment mechanism.

5.2.2. *Drones for vision-based operational modal analysis*

Most existing approaches for vision-based OMA relies on cameras to evaluate bridge displacements by tracking pixel movements across video frames using specialized algorithms. After obtaining the displacement time history, system identification methods are applied to extract the modal parameters. However, this approach is prone to errors caused by unintended drone movements and vibrations. To address these issues, stabilization techniques such as fixed-point tracking, inertial compensation, or high-pass filtering can be employed to reduce the impact of these disturbances.

To date, most studies in this field have focused on laboratory-scale mock-ups or small-scale pedestrian bridges, which are typically more flexible and exhibit more pronounced displacements than medium-span reinforced concrete bridges. Additionally, environmental factors can significantly impact the performance of point tracking in vision-based OMA. For example, wind can amplify drone vibrations, compromising the stability required for precise measurements, while low illumination conditions can deteriorate image quality, further hindering tracking accuracy. To date, most research in this area has focused on laboratory mock-ups or small-scale pedestrian bridges, which are inherently more flexible and exhibit greater displacements than medium-span reinforced concrete bridges. This focus limits the applicability of current findings to more rigid structures. To the authors' knowledge, field tests using drones for vision-based OMA on medium-span reinforced concrete bridges have not yet been conducted. Fig. 10 illustrates the typical process for obtaining modal parameters, which involves several steps that can be approached using different methodologies. Each step is outlined in detail below to provide a comprehensive understanding of the overall procedure.

STEP 1: Video acquisition. The input video for vision-based OMA is typically acquired using cameras mounted on drones. These cameras are usually the ones provided by the drone manufacturer, with resolutions ranging from 1280 × 720 to 4096 × 2160 pixels and frame rates between 24 and 90 frames per second. However, the influence of different camera resolutions on the accuracy of modal parameter extraction has not been thoroughly explored in the literature. Regarding frame rate, it is important to note that the maximum trackable frequency (Nyquist Frequency) is limited to half the sampling rate, highlighting the importance of selecting an appropriate frame rate based on the expected frequency range of the monitored structure. The distance between the drone and the target is a tradeoff between accuracy in capturing displacement and the possibility of capturing a wider area of the bridge.

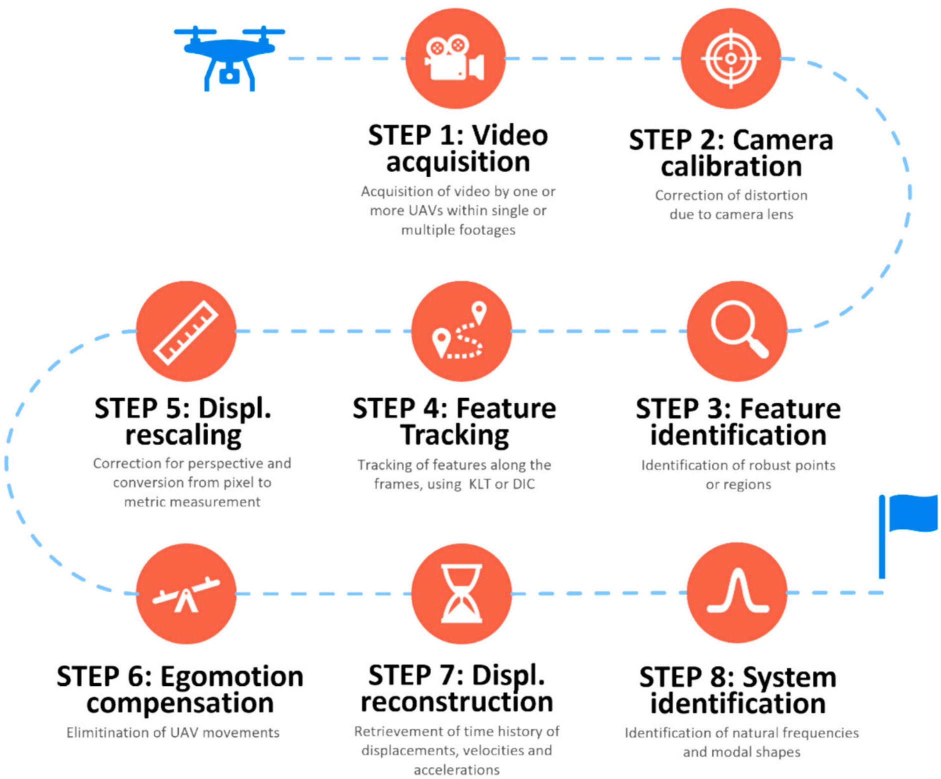

Fig. 10. Vision-based modal analysis flowchart.

Usually, distances between the camera and the target are in the range 1-5 m. Bolognini et al. [35] propose synchronizing videos captured simultaneously by multiple drones, each covering partially overlapping regions of the structure. This method enables accurate displacement measurements over a wider area without altering the camera-to-target distance, facilitating more reliable and detailed extraction of modal shapes. Similarly, Hoskere et al. [30] utilize a single drone to record videos of different bridge portions at different times. The information from these recordings is then combined to produce a comprehensive analysis of the structure.

STEP 2: Camera calibration. Camera calibration is performed to remove the possible lens distortion induced by the wide-angle lens, which are usually adopted for consumer-grade cameras. Yoneyama et al. [49] calibrated the camera using a checkerboard pattern with known geometry. The calibration process is made following Zhang [120]. Usually, the Pinhole Camera Model is used. The pinhole camera parameters are represented in a 3-by-4 matrix called the camera matrix. The matrix allows for passing from 2D camera coordinates to 3D world coordinates and vice-versa. The calibration of the matrix involves the detection of three types of parameters: extrinsic (rotation and translation), intrinsic (camera focal length and optical center) and distortional (to correct the curvature of the image).

STEP 3: Feature identification. The first issue to be addressed involves the tracking of selected points to estimate the displacement. One of the most used algorithms is the KLT tracking algorithm [48]. It tracks selected features of an image across several time instants by exploiting the notion of spatial intensity. Firstly, it is necessary to select the proper features to be tracked. To this aim, Bolognini et al. [35] and Hoskere et al. [30] exploit the Harris corner detection algorithm [121], which creates a tracking point wherever a corner is found. Another approach, followed by Weng et al. [50] involves the use of binary robust invariant scalable keypoints (BRISK), proposed by Leutenegger et al. [122].

STEP 4: Feature tracking. Once the keypoints are identified, a patch around the keypoint is selected, and the displacement of the patch over time is estimated by the KLT tracking algorithm, through the computation of a motion vector. The motion vector indicates the necessary shift of the selected patch that minimizes the sum of squared differences between the brightness of each point in the original and the shifted patch. The minimization is performed through a least-square estimation.

For feature tracking, some studies exploit fiducial markers, such as ArUco markers [123]. An ArUco marker is composed of alternations of black squares and white spaces; the position of black squares determines its identifier exactly as in the case of QR codes. Fiducial markers can ease the detection of invariant features by the Harris detection algorithm when the structure does not present easy-to-detect features (defects, junctions, welding spots, etc.). In the latter case, as shown by Bolognini et al. [35] the comparison of fiducial markers with "natural" markers yields no significant difference.

As an alternative to KLT tracking for STEP 4, DIC can be used [74]. DIC offers a robust optical method for tracking and image registration. DIC is designed for accurate 2D and 3D measurement of changes in images, relying on cross-correlation techniques between successive images. Also, this method is recognized for its ability to capture strain distribution. For vibrational monitoring applications [32,124], DIC is typically employed to estimate the displacement vector. This is achieved by minimizing the correlation coefficient between two image frames [124].

The use of different tracking algorithms involves tradeoffs between accuracy and computational burden. The KLT tracker is efficient for real-time tracking in controlled settings, making it suitable for basic displacement and frequency analysis, but it is sensitive to noise, lighting changes, and large deformations. DIC offers high accuracy for full-field displacement and strain measurements, making it ideal for detailed structural monitoring; however, its computational intensity limits its applicability in real-time scenarios. Zernike moments are robust for shape recognition and resistant to noise but are less precise for displacement analysis, with computational efficiency varying based on implementation. Overall, KLT is best for speed, DIC excels in precision for deformation analysis, and Zernike moments are effective for robust shape tracking under noise.

STEP 5: Displacement rescaling. The outcome of the KLT tracking or DIC is a time history of displacement of selected points, expressed in pixels. The measure can be easily converted in millimeters through a scale factor, that is obtained either by comparison with a known dimension (e.g. a bolt on the bridge) or by calculating the distance drone-bridge and exploiting trigonometry.

STEP 6: Egomotion compensation. Following this, drone movements, often referred to as egomotion, must be compensated. Even though cameras are partially decoupled from the drones through the use of a gimbal, they still experience some effects from the drone's oscillations. As a result, the time history of displacements is affected by the relative movement of the camera. Different approaches have been proposed to compensate for this.

- **Visual-based**. Yoon et al. [29] performed natural feature tracking to estimate the displacement of the targets, and compensated egomotion by estimating it for fixed reference points in the background. Similar procedures, based on the compensation with reference, exist [125]. Wu et al. [124] accounted for the camera rotation using the technique of homography. Vision-based compensation approaches require tracking the undeformed regions of the structure in the video frame, which can be a challenge in case of limited pixel resolution. Moreover, it is necessary to choose the points used for compensation and to accurately measure on the field the distances from them to the drone, which might be a complex, time-consuming and non-standardized task.
- **Inertial-based**. Weng et al. [50] used the IMU to compensate a posteriori for the camera movements, by subtracting the relative component due to camera movement from the measured displacements. Relative camera movements account for camera rotation (which is evaluated through a frequency ponderation of accelerometric and gyroscopic measurements) and camera translation. In the experimental setup, the egomotion compensation approach has demonstrated effective performance at frequencies below 1 Hz. It must be remarked that this approach relies on the precision of the accelerometric data, which might suffer from drift and might not be too reliable, especially in low-cost drones. Moreover, some commercial off-the-shelf drones do not allow the user to extract accelerometric data.
- **Frequency-based**. Hoskere et al. [30] and Bolognini et al. [35] employed frequency filtering to address egomotion in drone-based modal analysis. His method assumes that the natural frequencies of the bridge do not overlap with the primary spectral components associated with the camera's displacement. By separating these motion types through frequency domain filtering, the accuracy of the analysis is significantly improved [29,35]. This assumption is often valid for many civil structures. Drone oscillations caused by wind or stabilization inaccuracies typically occur at low frequencies (generally below 2 Hz), while noise from drone blade rotation is concentrated at much higher frequencies, around 80 Hz. The natural frequencies of most bridges fall between these two ranges, making it possible to isolate structural vibrations by applying band-pass filtering to the displacement data. This method is straightforward and effective for filtering out egomotion-related noise; however, it has limitations. Specifically, it cannot reliably capture natural frequencies below 1-2 Hz, which are common for slender or flexible bridges.

STEP 7. Displacement reconstruction. Rescaled and compensated displacement time histories are finally obtained, starting from the rescaled results obtained in Step 5 and removing the egomotion effect as obtained in Step 6. Displacements time histories should also be synchronized if they are obtained simultaneously from different drones [35].

STEP 8. System identification Finally, OMA techniques are applied to extract frequencies and modal shapes. Some studies identify natural frequencies through peak-picking but do not extract modal shapes [33,35]. Other studies utilize time-domain identification methods to derive modal shapes from observed displacement data. For example, Hoskere et al. [30] analyze displacement series from multiple points along a bridge, obtained through various acquisitions, to extract local modal shapes of the structure by means of the Natural Excitation Technique for the Eigen-System Realization Algorithm (NeXT ERA) [126]. The local modal shapes obtained from different points are then combined using the decentralized modal analysis method proposed by Sim et al. [127]. A related study by Haciefendioglu et al. [128] explores the reconstruction of modal shapes in the context of computer vision, utilizing a fixed camera rather than a drone. Their approach employs spectral analysis tools such as the Autoregressive Moving Average (ARMA) model and Enhanced Frequency Domain Decomposition (EFDD).

In principle, once natural frequencies are obtained, damage identification algorithms can be applied. However, current drone applications have primarily focused on extracting modal parameters and have not yet extended their analysis to include damage identification algorithms [124].

Table 4 summarizes the literature on vision-based methods for tracking displacements using drones. Several observations can be made from this synopsis. First, many of the methods have been tested under laboratory or controlled indoor conditions, where environmental factors such as intense sunlight, wind, and other challenges are minimized. Second, outdoor experiments primarily involve slender structures, such as pedestrian bridges, where displacements are on the order of tens of millimeters.

In-depth analyses are required to verify the feasibility of real-scale outdoor tests on real-world structures, evaluating whether the frequencies and displacement values of these structures are compatible with the limitations of current methods. Additionally, it would be valuable to conduct direct comparisons within the same experimental setup to study the influence of factors such as sampling time duration, camera resolution, distance to the target, and the effectiveness of different tracking and stabilization methods.

Considerations must be made regarding the feasibility of using drones for displacement detection. Data gathered from full-scale bridges [133] indicates that displacements are often below 10 mm. In such scenarios, drones employing vision-based methods may struggle to detect these small displacements, thereby limiting their applicability for OMA. In cases where dynamic displacements are undetectable, the only measurable parameter using vision-based methods might be the static deflection observed when a heavy vehicle or train crosses the bridge. While static deflection is more influenced by external factors, such as vehicle weight and temperature, than the modal parameters obtained through OMA, it still serves as a valuable indicator of structural health. By comparing normalized deflections (deflections divided by the applied load) within the framework of linear elasticity, potential damage can be inferred. For instance, an increase in normalized deflection over time may signal structural deterioration.

Given that bridge decks are often too stiff for drone-based CV techniques, these methods might find better applicability in monitoring slender elements, such as cables in cable-stayed bridges. Vision-based techniques can be used to measure the dynamic behavior of individual cables, enabling indirect estimation of their tension [134].

5.2.3. Drones for other non-destructive inspections

The versatility of drones enables them to carry a diverse array of sensors, making them capable of performing a wide range of non-destructive inspections, both contact and non-contact. While Sections 5.2.1 and 5.2.2 focused on contact-based and vision-based OMA, respectively, this section explores various approaches to conducting non-destructive inspections.

The integration of drones with Non-Destructive Testing (NDT)

Table 4
Comparison of vision-based vibrational monitoring techniques employing drones.

Reference	Tracking Method	Stabilization & Filtering Method	Type of setup	Drone Camera distance	Output	Accuracy	Order of magnitude of displacement
[29]	Non-Target KLT tracker (implemented by the author, 2016)	Stationary background tracking	Laboratory vibration simulation	4.6 m	Vertical displacement	2.14 mm RMSE (real bridge) compared to imposed displacement	<20 mm
[30]	ArUco fiducial markers & KLT tracker	High-pass filtering, and nonlinear optimization using the Levenberg–Marquardt Algorithm.	Laboratory + pedestrian bridge	≈ 5 m	Vertical displacement, Modal analysis and natural frequencies	<0.5 % (lab.) <1.6 % (real case) Compared to accelerometers	<20 mm
[33]	Zernike moment for edge detection and tracking	Normalized Cross-Correlation template matching (fixed background)	Laboratory (shaker)	1.5 m	Vertical displacements and frequencies	–	2,5 and 10 mm
[125]	Key-point tracking	Difference with a stationary object in the background	Steel plate (outdoor)	≈ 2 m	Displacement	Under a fixed camera (with an accuracy of 0.01 mm @ 3 m)	<60 mm
[124]	Digital Image Correlation (DIC)	3D coordinate reconstruction using fixed background object; compared with homography	Laboratory	3 m	Displacement, frequencies	0.66 % for the first frequency for 3D reconstruction with 1 m vertical difference camera-target	<15 mm
[35]	KLT tracking of selected points	2-drone synchronization + high pass filter @2 Hz	Steel cantilever (outdoor)	1.5 m	Frequencies	0.2 % for accelerometers	< 5-10 mm
[50]	Key-point KLT tracking	Drone-Embedded IMU	Uniaxial shaking table (indoor)	1.5 m	Displacement	3.1 mm compared to stationary KLT	< 20 mm
[129]	Target-based tracking	Laser from the ground sets a fixed spot on the bridge	Laboratory + long-span bridge	unknown	Displacement	<1 % on displacements compared with laser;	<10 mm
[130]	DIC compared with KLT tracking	CNN identifying fixed reference points in a backward wall	Small-scale bridge (indoor)	2 m	Displacement	–	<12 mm
[131]	KLT tracking or Mask R-CNN	Differences with fixed nearby objects	Laboratory +6 pedestrian bridges	≈ 2 m	Displacement, frequencies	<2 % for frequencies for accelerometers, but the peak in FFT for drones is almost invisible	< 5 mm
[132]	Grayscale matching	Drone tracking with a fixed camera	Outdoor mock-up	1.5 m	Frequencies, modal analysis	<0.15 Hz compared to accelerometers	unknown
[61]	Target tracking	Compensation with laser measurements	Pedestrian bridge	≈ 4 m	Displacement	<30 % on displacements compared to laser	100 mm

sensors involves the combined effort of robotics and monitoring technologies. Several studies focus their attention on the development of drone platforms and procedures to carry different NDT. Marcellini et al. [135] propose a semi-autonomous framework for NDT inspection with a tilting aerial platform, in which an octa-rotor drone is equipped with a robotic arm. Zhou et al. [136] propose a wall-sticking drone for NDT inspections of oblique planes. For the relative ease of operation, ultrasonic sensors are tested in different studies for integration with drones. Mattar & Kalai [137] and Dahlstrom [138] propose a wall-sticking drone carrying an ultrasonic sensor, to measure coating thickness in direct contact with the surface of interest.

Schewe et al. [139] and Garg et al. [31] combine drones with LDV technology to extract information on transverse displacement and vibration, respectively. Specifically, in Garg et al. [31], the drone directly carries the LDV equipment, enabling it to capture vibration data in proximity to the target structure. Conversely, Schewe et al. [139] employ a different approach: the LDV remains ground-based, while the drone carries a mirror that serves as an optical beam steering unit. This setup enhances the optical precision of the LDV measurements by allowing the beam to be directed more accurately, even in complex or hard-to-reach areas.

Computer vision can be utilized to extract valuable structural information beyond vibrational monitoring. Ri et al. [140] employ vision-based techniques with a drone to measure bridge displacements by analyzing phase information. Similarly, Zhuge et al. [141] and Ellenberg et al. [26] measure bridge vertical deflection, while Jalinoos et al. [142] extend this capability to include both deflections and rotations. Kumarapu et al. [143] use DIC to extract strain fields from drone-captured images. As with vibrational data, it is important to note that the magnitude of displacements and strains under operational conditions may fall below the resolution of these techniques, particularly for stiff bridges.

The integration of drones with non-destructive testing (NDT) sensors holds significant potential to increase the frequency and efficiency of NDT inspections, especially in hard-to-reach areas. To fully realize this potential, drones must evolve into multifunctional robotic tools that can support standardized inspections across various bridge components using a diverse array of NDT tools. Additionally, it is critical to address the interaction between drones and the attached sensors. Drone-induced disturbances, such as vibrations or positional instability, can impact the accuracy of measurement results. Future research should prioritize developing methods to mitigate these effects, drawing inspiration from egomotion compensation techniques used in vision-based OMA.

5.3. Application examples: vision-based vibrational monitoring

For clarity, some illustrative results in the field of vision-based vibrational monitoring are presented, drawing on findings from Bolognini et al. [35] and Yan et al. [144], shown in Fig. 11, Fig. 12 and Fig. 13. These results highlight several phenomena commonly observed in drone-based modal analysis. First, in both studies, the experiments were performed under controlled conditions using scaled structures with relatively high displacement ranges. External excitation, such as a hammer impact, was applied to induce measurable structural responses.

Fig. 11. Experimental setup (a), tracking time history (b) and FFT (c), from [35].

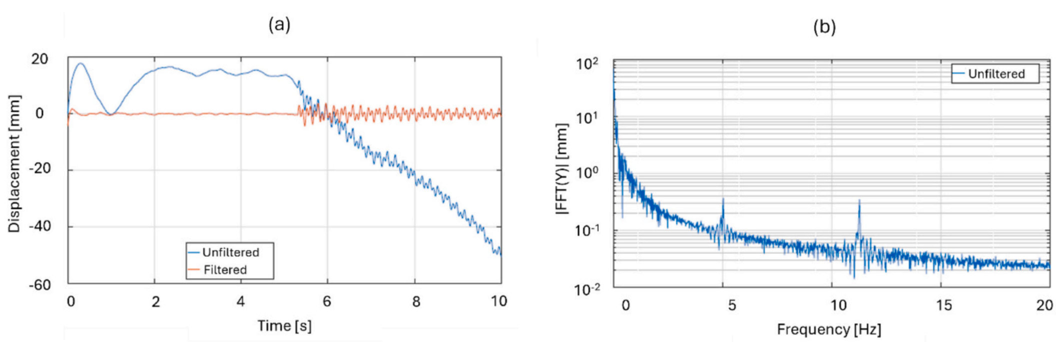

Fig. 12. Tracking time history (a) and FFT (b), from [35].

Second, unfiltered time histories from the experiments — depicted in Fig. 12 (a) and Fig. 13 (b) — show low-frequency oscillations attributed to drone dynamics. These oscillations overlap with the higher-frequency vibrations of the structure, which occur in response to the external excitation. Furthermore, the FFT plot in Fig. 12 *(b)* reveals distinct peaks corresponding to the structure's natural frequencies, standing out despite the noise introduced by drone-induced disturbances. Conversely, Fig. 13 *(b)* illustrates the effectiveness of egomotion compensation in isolating the true structural vibration time history. The compensation process filters out drone-related disturbances, with the resulting signal (identified as IMF 1) clearly representing the structural vibrations.

5.4. Challenges and research directions in damage detection

The use of drones for bridge damage detection holds significant untapped potential. As hardware and software advancements progress, innovative academic approaches are expected to evolve into standardized inspection practices. Starting from improvements in drone technology, longer-lasting batteries will enable more detailed inspection, or to inspect larger structures with a single flight. A more precise positioning system and inertial measurements will result in stable flight, increasing the quality of videos and photos taken from the drone, even more if assisted by high-quality camera lenses. Thus, information coming from visual sensors is expected to be less uncertain, both in the case of surface damage detection and vision-based modal analysis. Moreover, the increase in the degree of automation will certainly open the path towards drones acting as aerial manipulators, enabling the integration with NDT sensors and substituting manual operators for dangerous tasks, such as the installation of sensors below the bridge.

Concerning information technology, there is a pressing need to improve AI and CV algorithms towards increased computational efficiency, having multiple uses in the field of image processing and feature identification. Technological advancement in this field will allow for the creation of highly refined 3D photogrammetric point clouds already containing detailed information on surface damage, as detected by ML algorithms on 2D pictures. Moreover, path planning algorithms will be crucial to selecting the most effective paths within the flight autonomy time limits. Finally, onboard and real-time damage detection algorithms will provide an effective solution for further investigation during the inspection. The integration with virtual reality environments constitutes a further opportunity to increase the efficiency of inspections [4].

The use of drones for automated surface damage detection emerges, from the examination of existing literature, as a promising field that will gain more and more importance as hardware and procedures improve. Among the benefits of using drones for such inspections are the ability to access hard-to-reach areas with ease, the rapid collection of a large number of images, and the enhanced safety conditions provided for the operator. The limitations concern especially regulatory aspects, as drones often cannot fly over restricted areas where they might be a hazard (e.g. over motorways). Challenges for the future regard the improvement of surface damage detection algorithms, to increase their

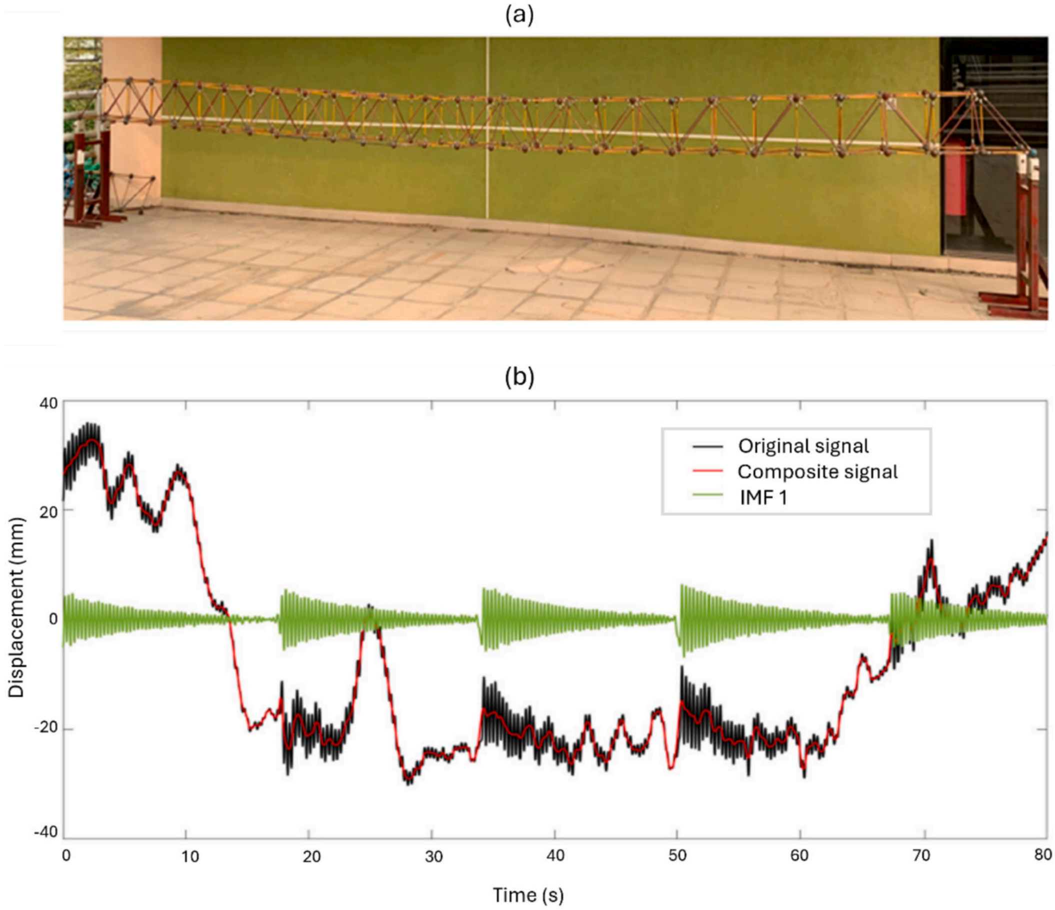

Fig. 13. Experimental setup (a) and time history (b), adapted from [124,144].

capability of detecting with precision a wide range of defects, along with a reduced computational burden.

Finally, particular attention should be dedicated to the topic of vision-based OMA. Firstly, it is necessary to focus on the topic of egomotion compensation for vision-based vibrational monitoring Beyond the aforementioned methods (visual-based, frequency-based and inertial based), future research should explore hybrid approaches that combine multiple techniques, which have shown significant potential for improving egomotion compensation. For instance, integrating inertial and visual data, often referred to as sensor fusion, can leverage the complementary strengths of both modalities to improve compensation accuracy. Inertial sensors, such as accelerometers and gyroscopes, provide high-frequency data on camera motion but are prone to cumulative drift over time. Visual data, on the other hand, is less susceptible to drift and provides spatial context but may be impacted by environmental factors like lighting changes, motion blur, or occlusions. By fusing these data sources, it is possible to mitigate the weaknesses of each, resulting in a more robust estimation of camera egomotion. Techniques for sensor fusion can include Kalman filtering [145], which integrates data streams in real-time, and more advanced methods like nonlinear optimization and factor graph-based approaches [146]. These methods can jointly estimate pose and compensate for motion with high precision, even in challenging environments. Additionally, using visual-inertial odometry was proven effective in related applications such as autonomous navigation and robotics, and its adaptation to structural monitoring could yield substantial benefits [147]. Furthermore, with a focus on vision-based and inertial-based compensation deep learning approaches have shown considerable potential in motion estimation and compensation in domains such as autonomous driving and video stabilization. Neural networks can be trained to learn complex motion patterns and distinguish between camera movement and structural vibrations, potentially bypassing the need for explicit motion modeling. For instance, CNNs could be employed to predict egomotion from sequences of visual and inertial data, providing compensation that is adaptive to varying conditions [148].

Secondly, it is necessary to assess the range of applicability of drone technology for medium and long-span bridges. Refining motion compensation procedures might also help in extracting natural frequencies with precision when displacement range is limited. Yet, the influence of factors such as the drone distance from the bridge, the camera resolution, the tracking method and the duration of the video need to be systematically discussed in the literature. Another issue involves the extraction of modal shapes, which may require the use of multiple and simultaneous videos. To this aim, the use of swarms of drones might be essential. In alternative to vision-based OMA approaches, also contact-based OMA approach exploiting drones is an open field of research. Contrary to traditional OMA approaches based on fixed sensors, where data is sampled continuously, it is expected that, when using drones, modal information will be sampled only a few times a year and the sensing devices will be reused for different structures. That will reduce the economic and environmental costs of SHM through a reduction of non-renewable resources exploitation, and of the amount of electronic waste. To cope with infrequent data sampling, further investigation on damage detection and the removal of environmental effects, using few observations is needed. An even broader topic concerns the use of the obtained damage information for supporting decision-makers in planning maintenance for the infrastructural network. The economic aspect of drone-based inspections should also be considered, balancing inspection costs and benefits, based on the evaluation of the Value of Information collected by the drones [149].

6. Conclusions

This comprehensive literature review highlights that the full potential of drone operations in bridge management has yet to be fully realized, indicating significant opportunities for future development. Drone-aided visual inspections are already providing substantial benefits, including easier image capture, enhanced safety for operators, and improved quality of inspection results. Current research is further advancing these capabilities through the integration of automated damage detection and Bridge Information Modeling.

The key conclusions of this paper are here shown:

- Visual inspection technologies have reached a relatively mature stage, with further progress expected in the realm of information technology, heading towards fully automated inspections using AI for damage recognition. However, the effectiveness of remotely driven drone-based bridge monitoring hinges on the availability of a reliable and high-bandwidth communication network to facilitate the transmission of images and video streams to remote locations. Inspection planning remains crucial to guarantee the cost-effectiveness, efficacy and quality of gathered data.
- Several important studies focus on increasing network reliability in the context of the IoD, utilizing cutting-edge communication technologies and integrating drone swarms into high-capacity wireless networks, such as the latest-generation cellular networks. This approach requires careful consideration of challenges such as inter-drone communication, the establishment of reliable air-to-air (A2A) and air-to-ground (A2G) communication channels, ensuring data confidentiality and security, and managing the high mobility of drones, which frequently alters network topology and channel quality. Although various strategies have been proposed to address these issues, they must be tailored to the specific use cases at hand.
- Drone-assisted visual modal analysis emerges as a promising research area, offering a cost-effective and efficient method for extracting modal parameters to evaluate structural conditions. However, several unresolved questions remain, particularly concerning the compatibility of the currently available drone-based monitoring technologies with the structural behaviors under investigation. Furthermore, more research is required for refined ego-motion compensation.
- For all the proposed inspection outcomes, advancements in hardware—such as improved batteries and lightweight equipment—and in communication technologies—like enhanced transmission and remote-control capabilities—are expected to significantly expand the applications of drones. In particular, the integration of drones with manipulating capabilities will enhance the possibility of contact-based inspection.

These developments lay the groundwork for fully remote, centralized operations, which offer substantial advantages in terms of cost, precision, quality, and the volume of data collected. This represents a significant improvement over traditional methods that rely on human intervention or traditional contact-type sensors, underscoring the transformative potential of drone technology in bridge inspection and management.

CRediT authorship contribution statement

Tommaso Panigati: Writing – original draft, Methodology, Investigation, Conceptualization. **Mattia Zini:** Writing – original draft, Methodology, Investigation, Conceptualization. **Domenico Striccoli:** Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization. **Pier Francesco Giordano:** Writing – review & editing, Writing – original draft, Supervision, Conceptualization. **Daniel Tonelli:** Writing – review & editing, Supervision, Conceptualization. **Maria Pina Limongelli:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Daniele Zonta:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

References

[1] K. Wardhana, F.C. Hadipriono, Analysis of recent bridge failures in the United States, J. Perform. Constr. Facil. 17 (2003), https://doi.org/10.1061/(asce)0887-3828(2003)17:3(144).
[2] G. Zhang, Y. Liu, J. Liu, S. Lan, J. Yang, Causes and statistical characteristics of bridge failures: a review, J. Traffic Transp. Eng. (English Ed.) 9 (2022), https://doi.org/10.1016/j.jtte.2021.12.003.
[3] D.M. Frangopol, Y. Dong, S. Sabatino, Bridge life-cycle performance and cost: analysis, prediction, optimisation and decision-making, Struct. Infrastruct. Eng. 13 (2017), https://doi.org/10.1080/15732479.2016.1267772.
[4] F. Luleci, F.N. Catbas, Bringing site to the office: decision-making in infrastructure management through virtual reality, Autom. Constr. 166 (2024) 105675, https://doi.org/10.1016/j.autcon.2024.105675.
[5] F. Magalhães, A. Cunha, E. Caetano, Vibration based structural health monitoring of an arch bridge: from automated OMA to damage detection, Mech. Syst. Signal Process. 28 (2012), https://doi.org/10.1016/j.ymssp.2011.06.011.
[6] J. Kullaa, Distinguishing between sensor fault, structural damage, and environmental or operational effects in structural health monitoring, Mech. Syst. Signal Process. 25 (2011), https://doi.org/10.1016/j.ymssp.2011.05.017.
[7] J. Pasha, Z. Elmi, S. Purkayastha, A.M. Fathollahi-Fard, Y.E. Ge, Y.Y. Lau, M. A. Dulebenets, The drone scheduling problem: a systematic state-of-the-art review, IEEE Trans. Intell. Transp. Syst. 23 (2022), https://doi.org/10.1109/TITS.2022.3155072.
[8] P. Boccadoro, D. Striccoli, L.A. Grieco, An extensive survey on the internet of drones, Ad Hoc Netw. 122 (2021), https://doi.org/10.1016/j.adhoc.2021.102600.
[9] S. Feroz, S.A. Dabous, Uav-based remote sensing applications for bridge condition assessment, Remote Sens. 13 (2021), https://doi.org/10.3390/rs13091809.
[10] P. Nooralishahi, C. Ibarra-Castanedo, S. Deane, F. López, S. Pant, M. Genest, N. P. Avdelidis, X.P.V. Maldague, Drone-based non-destructive inspection of industrial sites: a review and case studies, Drones 5 (2021), https://doi.org/10.3390/drones5040106.
[11] B. Hubbard, S. Hubbard, Unmanned aircraft systems (Uas) for bridge inspection safety, Drones 4 (2020), https://doi.org/10.3390/drones4030040.
[12] I.H. Kim, S. Yoon, J.H. Lee, S. Jung, S. Cho, H.J. Jung, A comparative study of bridge inspection and condition assessment between manpower and a UAS, Drones 6 (2022), https://doi.org/10.3390/drones6110355.
[13] S.S.C. Congress, J. Escamilla, H. Chimauriya, A.J. Puppala, Eye in the sky: 360° inspection of bridge infrastructure using uncrewed aerial vehicles (UAVs), Transp. Res. Rec. (2023), https://doi.org/10.1177/03611981231185138.
[14] N. Hossein Motlagh, T. Taleb, O. Arouk, Low-altitude unmanned aerial vehicles-based internet of things services: comprehensive survey and future perspectives, IEEE Internet Things J. 3 (2016), https://doi.org/10.1109/JIOT.2016.2612119.
[15] Y. Tian, C. Chen, K. Sagoe-Crentsil, J. Zhang, W. Duan, Intelligent robotic systems for structural health monitoring: applications and future trends, Autom. Constr. 139 (2022), https://doi.org/10.1016/j.autcon.2022.104273.
[16] S. Poorghasem, Y. Bao, Review of robot-based automated measurement of vibration for civil engineering structures, Measurement (Lond) 207 (2023), https://doi.org/10.1016/j.measurement.2022.112382.
[17] R. Zinno, S.S. Haghshenas, G. Guido, K. Rashvand, A. Vitale, A. Sarhadi, The state of the art of artificial intelligence approaches and new technologies in structural health monitoring of bridges, Appl. Sci. (Switzerland) 13 (2023), https://doi.org/10.3390/app13010097.
[18] C. Ferraris, G. Amprimo, G. Pettiti, Computer vision and image processing in structural health monitoring: overview of recent applications, Signals 4 (2023), https://doi.org/10.3390/signals4030029.

[19] Y.-J. Cha, R. Ali, J. Lewis, O. Büyüköztürk, Deep learning-based structural health monitoring, Autom. Constr. 161 (2024), https://doi.org/10.1016/j.autcon.2024.105328.

[20] S. Sony, S. Laventure, A. Sadhu, A literature review of next-generation smart sensing technology in structural health monitoring, Struct. Control. Health Monit. 26 (2019), https://doi.org/10.1002/stc.2321.

[21] B.F. Spencer, V. Hoskere, Y. Narazaki, Advances in computer vision-based civil infrastructure inspection and monitoring, Engineering 5 (2019), https://doi.org/10.1016/j.eng.2018.11.030.

[22] A. Zona, Vision-based vibration monitoring of structures and infrastructures: An overview of recent applications, Infrastructures (Basel) 6 (2021), https://doi.org/10.3390/infrastructures6010004.

[23] K. Luo, X. Kong, J. Zhang, J. Hu, J. Li, H. Tang, Computer vision-based bridge inspection and monitoring: a review, Sensors 23 (2023), https://doi.org/10.3390/s23187863.

[24] T. Rakha, A. Gorodetsky, Review of unmanned aerial system (UAS) applications in the built environment: towards automated building inspection procedures using drones, Autom. Constr. 93 (2018), https://doi.org/10.1016/j.autcon.2018.05.002.

[25] J.F. Keane, S.S. Carr, A brief history of early unmanned aircraft, Johns Hopkins APL Tech. Digest (Appl. Phys. Lab.) 32 (2013).

[26] A. Ellenberg, L. Branco, A. Krick, I. Bartoli, A. Kontsos, Use of unmanned aerial vehicle for quantitative infrastructure evaluation, J. Infrastruct. Syst. 21 (2015), https://doi.org/10.1061/(asce)is.1943-555x.0000246.

[27] H. Yoon, V. Hoskere, J.W. Park, B.F. Spencer, Cross-correlation-based structural system identification using unmanned aerial vehicles, Sensors (Switzerland) 17 (2017), https://doi.org/10.3390/s17092075.

[28] D. Reagan, A. Sabato, C. Niezrecki, Feasibility of using digital image correlation for unmanned aerial vehicle structural health monitoring of bridges, Struct. Health Monit. 17 (2018), https://doi.org/10.1177/1475921717735326.

[29] H. Yoon, J. Shin, B.F. Spencer, Structural displacement measurement using an unmanned aerial system, Comput. Aided Civ. Inf. Eng. 33 (2018), https://doi.org/10.1111/mice.12338.

[30] V. Hoskere, J.-W. Park, H. Yoon, B.F. Spencer, Vision-based modal survey of civil infrastructure using unmanned aerial vehicles, J. Struct. Eng. (United States) 145 (2019), https://doi.org/10.1061/(ASCE)ST.1943-541X.0002321.

[31] P. Garg, R. Nasimi, A. Ozdagli, S. Zhang, D.D.L. Mascarenas, M.R. Taha, F. Moreu, Measuring transverse displacements using unmanned aerial systems laser doppler vibrometer (UAS-LDV): development and field validation, Sensors (Switzerland) 20 (2020), https://doi.org/10.3390/s20216051.

[32] G. Chen, Q. Liang, W. Zhong, X. Gao, F. Cui, Homography-based measurement of bridge vibration using UAV and DIC method, Measurement (Lond) 170 (2021), https://doi.org/10.1016/j.measurement.2020.108683.

[33] X. Bai, M. Yang, UAV based accurate displacement monitoring through automatic filtering out its camera's translations and rotations, J. Build. Eng. 44 (2021), https://doi.org/10.1016/j.jobe.2021.102992.

[34] Y. Tian, C. Zhang, S. Jiang, J. Zhang, W. Duan, Noncontact cable force estimation with unmanned aerial vehicle and computer vision, Comput. Aided Civ. Inf. Eng. 36 (2021) 73–88, https://doi.org/10.1111/mice.12567.

[35] M. Bolognini, G. Izzo, D. Marchisotti, L. Fagiano, M.P. Limongelli, E. Zappa, Vision-based modal analysis of built environment structures with multiple drones, Autom. Constr. 143 (2022), https://doi.org/10.1016/j.autcon.2022.104550.

[36] I.H. Kim, H. Jeon, S.C. Baek, W.H. Hong, H.J. Jung, Application of crack identification techniques for an aging concrete bridge inspection using an unmanned aerial vehicle, Sensors (Switzerland) 18 (2018), https://doi.org/10.3390/s18061881.

[37] S. Yoon, S. Lee, S. Kye, I.H. Kim, H.J. Jung, B.F. Spencer, Seismic fragility analysis of deteriorated bridge structures employing a UAV inspection-based updated digital twin, Struct. Multidiscip. Optim. 65 (2022), https://doi.org/10.1007/s00158-022-03445-0.

[38] S. Carroll, J. Satme, S. Alkharusi, N. Vitzilaios, A. Downey, D. Rizos, Drone-based vibration monitoring and assessment of structures, Appl. Sci. (Switzerland) 11 (2021), https://doi.org/10.3390/app11188560.

[39] C. Eschmann, T. Wundsam, Web-based georeferenced 3D inspection and monitoring of bridges with unmanned aircraft systems, J. Surv. Eng. 143 (2017), https://doi.org/10.1061/(asce)su.1943-5428.0000221.

[40] M. Gordan, Z. Ismail, K. Ghaedi, Z. Ibrahim, H. Hashim, H.H. Ghayeb, M. Talebkhah, A brief overview and future perspective of unmanned aerial systems for in-service structural health monitoring, Eng. Adv. 1 (2021), https://doi.org/10.26855/ea.2021.06.002.

[41] S. Sreenath, H. Malik, N. Husnu, K. Kalaichelavan, Assessment and use of unmanned aerial vehicle for civil structural health monitoring, Procedia Comput. Sci. (2020), https://doi.org/10.1016/j.procs.2020.03.174.

[42] I. Mosly, Applications and issues of unmanned aerial systems in the construction industry, Int. J. Construct. Eng. Manag. 6 (2017), https://doi.org/10.5923/j.ijcem.20170606.02.

[43] G. Morgenthal, N. Hallermann, J. Kersten, J. Taraben, P. Debus, M. Helmrich, V. Rodehorst, Framework for automated UAS-based structural condition assessment of bridges, Autom. Constr. 97 (2019), https://doi.org/10.1016/j.autcon.2018.10.006.

[44] L. Duque, J. Seo, J. Wacker, Synthesis of unmanned aerial vehicle applications for infrastructures, J. Perform. Constr. Facil. 32 (2018), https://doi.org/10.1061/(asce)cf.1943-5509.0001185.

[45] S. Perez Jimeno, J. Capa Salinas, J.A. Perez Caicedo, M.A. Rojas Manzano, An integrated framework for non-destructive evaluation of bridges using UAS: a case study, J. Build. Pathol. Rehabil. 8 (2023), https://doi.org/10.1007/s41024-023-00299-x.

[46] J. Seo, L. Duque, J. Wacker, Drone-enabled bridge inspection methodology and application, Autom. Constr. 94 (2018), https://doi.org/10.1016/j.autcon.2018.06.006.

[47] D. Hu, T. Yee, D. Goff, Automated crack detection and mapping of bridge decks using deep learning and drones, J. Civ. Struct. Heal. Monit. 14 (2024), https://doi.org/10.1007/s13349-023-00750-0.

[48] B.D. Lucas, T. Kanade, Iterative image registration technique with an application to stereo vision, in: 7th Joint International Conference on Artifical Intelligence, Vancouver, 1981.

[49] S. Yoneyama, Basic principle of digital image correlation for in-plane displacement and strain measurement, Adv. Compos. Mater. 25 (2016), https://doi.org/10.1080/09243046.2015.1129681.

[50] Y. Weng, Z. Lu, X. Lu, B.F. Spencer, Visual–inertial structural acceleration measurement, Comput. Aided Civ. Inf. Eng. 37 (2022), https://doi.org/10.1111/mice.12831.

[51] E. Tomassini, E. García-Macías, E. Reynders, F. Ubertini, Model-assisted clustering for automated operational modal analysis of partially continuous multi-span bridges, Mech. Syst. Signal Process. 200 (2023), https://doi.org/10.1016/j.ymssp.2023.110587.

[52] R. Steffen, W. Forstner, On visual real time mapping for unmanned aerial vehicles, in: The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. Vol. XXXVII. Part B3a. Beijing, 2008 (n.d.).

[53] A. Smaoui, Y. Yaddaden, R. Cherif, D. Lamouchi, Automated scanning of concrete structures for crack detection and assessment using a drone, in: 2022 IEEE 21st International Conference on Sciences and Techniques of Automatic Control and Computer Engineering, STA 2022 - Proceedings, 2022, https://doi.org/10.1109/STA56120.2022.10019224.

[54] Y. Zhao, B. Lu, M. Alipour, Optimized structural inspection path planning for automated unmanned aerial systems, Autom. Constr. 168 (2024) 105764, https://doi.org/10.1016/J.AUTCON.2024.105764.

[55] S. Perez Jimeno, J. Capa Salinas, J.A. Perez Caicedo, M.A. Rojas Manzano, An integrated framework for non-destructive evaluation of bridges using UAS: a case study, J. Build. Pathol. Rehabil. 8 (2023), https://doi.org/10.1007/s41024-023-00299-x.

[56] S. Dorafshan, R.J. Thomas, M. Maguire, Fatigue crack detection using unmanned aerial systems in fracture critical inspection of steel bridges, J. Bridg. Eng. 23 (2018), https://doi.org/10.1061/(asce)be.1943-5592.0001291.

[57] D. González-Aguilera, S. Lagüela, P. Rodríguez-Gonzálvez, D. Hernández-López, Image-based thermographic modeling for assessing energy efficiency of buildings façades, Energ. Build. 65 (2013), https://doi.org/10.1016/j.enbuild.2013.05.040.

[58] A. Colantonio, G. McIntosh, The differences between large buildings and residential infrared thermographic inspections is like night and day, in: 11th Canadian Conference on Building Science and Technology, 2007.

[59] I. Lizarazo, V. Angulo, J. Rodríguez, Automatic mapping of land surface elevation changes from UAV-based imagery, Int. J. Remote Sens. 38 (2017), https://doi.org/10.1080/01431161.2016.1278313.

[60] M. Gharibi, R. Boutaba, S. Waslander, Internet of drones, IEEE Access 4 (2016), https://doi.org/10.1109/ACCESS.2016.2537208.

[61] R. Nasimi, F. Moreu, G.M. Fricke, Sensor equipped UAS for non-contact bridge inspections: field application, Sensors 23 (2023), https://doi.org/10.3390/s23010470.

[62] S. Park, L. Zhang, S. Chakraborty, Battery assignment and scheduling for drone delivery businesses, in: Proceedings of the International Symposium on Low Power Electronics and Design, 2017, https://doi.org/10.1109/ISLPED.2017.8009165.

[63] K.A. Swieringa, C.B. Hanson, J.R. Richardson, J.D. White, Z. Hasan, E. Qian, A. Girard, Autonomous battery swapping system for small-scale helicopters, in: Proc IEEE Int Conf Robot Autom, 2010, https://doi.org/10.1109/ROBOT.2010.5509165.

[64] S. Duan, X. Lu, H. Wu, H. Zhang, Z. Zhang, G. Wang, Unmanned aerial vehicle wireless power transfer system for long-distance transmission line patrol, in: PEAC 2022 - 2022 IEEE International Power Electronics and Application Conference and Exposition, Proceedings, 2022, https://doi.org/10.1109/PEAC56338.2022.9959186.

[65] S. Atoev, O.H. Kwon, S.H. Lee, K.R. Kwon, An efficient SC-FDM modulation technique for a UAV communication link, Electronics (Switzerland) 7 (2018), https://doi.org/10.3390/electronics7120352.

[66] C. Yan, L. Fu, J. Zhang, J. Wang, A comprehensive survey on UAV communication channel modeling, IEEE Access 7 (2019), https://doi.org/10.1109/ACCESS.2019.2933173.

[67] X. Tan, Z. Zuo, S. Su, X. Guo, X. Sun, D. Jiang, Performance analysis of routing protocols for UAV communication networks, IEEE Access 8 (2020), https://doi.org/10.1109/ACCESS.2020.2995040.

[68] F. Meng, F. Bu, Y. Wang, Optimization of the UAV network routing protocol based on the ant swarm algorithm, in: 2023 IEEE 3rd International Conference on Electronic Technology, Communication and Information, ICETCI 2023, 2023, https://doi.org/10.1109/ICETCI57876.2023.10176567.

[69] P. Pekarcik, E. Chovancova, M. Havrilla, M. Hasin, Security analysis of attacks on UAV, in: 2023 IEEE 21st World Symposium on Applied Machine Intelligence and Informatics, SAMI 2023 - Proceedings, 2023, https://doi.org/10.1109/SAMI58000.2023.10044500.

[70] W. Wang, Z. Han, T.R. Gadekallu, S. Raza, J. Tanveer, C. Su, Lightweight blockchain-enhanced mutual authentication protocol for UAVs, IEEE Internet Things J. 11 (2024), https://doi.org/10.1109/JIOT.2023.3324543.
[71] G. Geraci, A. Garcia-Rodriguez, M.M. Azari, A. Lozano, M. Mezzavilla, S. Chatzinotas, Y. Chen, S. Rangan, M. Di Renzo, What will the future of UAV cellular communications be? A flight from 5G to 6G, IEEE Commun. Surv. Tutor. 24 (2022), https://doi.org/10.1109/COMST.2022.3171135.
[72] D. Si, R.M. Edwards, Y. Geng, XBee latency analysis for drone mounted machine control over wireless communication channels, in: 15th European Conference on Antennas and Propagation, EuCAP 2021, 2021, https://doi.org/10.23919/EuCAP51087.2021.9411478.
[73] T.Y. Kim, J.W. Cho, J.H. Kim, Performance evaluation of wireless LAN for UAS communication, in: International Conference on Information Networking, 2021, https://doi.org/10.1109/ICOIN50884.2021.9333951.
[74] F. Fabra, C.T. Calafate, J.C. Cano, P. Manzoni, On the impact of inter-UAV communications interference in the 2.4 GHz band, in: 2017 13th International Wireless Communications and Mobile Computing Conference, IWCMC 2017, 2017, https://doi.org/10.1109/IWCMC.2017.7986413.
[75] M.K. Banafaa, O. Pepeoglu, I. Shayea, A. Alhammadi, Z.A. Shamsan, M.A. Razaz, M. Alsagabi, S. Al-Sowayan, A comprehensive survey on 5G-and-beyond networks with UAVs: applications, emerging technologies, regulatory aspects, research trends and challenges, IEEE Access 12 (2024), https://doi.org/10.1109/ACCESS.2023.3349208.
[76] S.K. Khan, U. Naseem, H. Siraj, I. Razzak, M. Imran, The role of unmanned aerial vehicles and mmWave in 5G: recent advances and challenges, Trans. Emerg. Telecommun. Technol. 32 (2021), https://doi.org/10.1002/ett.4241.
[77] M. Mozaffari, W. Saad, M. Bennis, M. Debbah, Communications and control for wireless drone-based antenna array, IEEE Trans. Commun. 67 (2019), https://doi.org/10.1109/TCOMM.2018.2871453.
[78] Z. Xiao, L. Zhu, Y. Liu, P. Yi, R. Zhang, X.G. Xia, R. Schober, A survey on millimeter-wave beamforming enabled UAV communications and networking, IEEE Commun. Surv. Tutor. 24 (2022), https://doi.org/10.1109/COMST.2021.3124512.
[79] R. Kunst, E. Pignaton, T. Zhou, H. Hu, Application of future 6G technology to support heavy data traffic in highly mobile networks, in: Proceedings - 2020 1st International Conference of Smart Systems and Emerging Technologies, SMART-TECH 2020, 2020, https://doi.org/10.1109/SMART-TECH49988.2020.00044.
[80] G. Castellanos, G. Vallero, M. Deruyck, L. Martens, M. Meo, W. Joseph, Evaluation of flying caching servers in UAV-BS based realistic environment, Veh. Commun. 32 (2021), https://doi.org/10.1016/j.vehcom.2021.100390.
[81] M.S. Haroon, F. Muhammad, G. Abbas, Z.H. Abbas, A.K. Hassan, M. Waqas, S. Kim, Interference management in ultra-dense 5G networks with excessive drone usage, IEEE Access 8 (2020), https://doi.org/10.1109/ACCESS.2020.2998494.
[82] F. Al-Turjman, J.P. Lemayian, S. Alturjman, L. Mostarda, Enhanced deployment strategy for the 5G drone-BS using artificial intelligence, IEEE Access 7 (2019), https://doi.org/10.1109/ACCESS.2019.2921729.
[83] Bluetooth, Bluetooth. (2003), Bluetooth Technology, 2003 [Online]. Available, https://www.bluetooth.com/.
[84] S. Banerji, R. Chowdhury, Wi-Fi & WiMAX: A Comparative Study, ArXiv, 2013, https://doi.org/10.48550/arXiv.1302.2247.
[85] The ZigBee Alliance, The ZigBee Alliance, Control Your World. (2002) [Online]. Available, http://www.zigbee.org/, 2002.
[86] E. Coelho, P. Carvalhal, M. Ferreira, L. Silva, H. Almeida, J. Afonso, C. Santos, Distributed sensing and actuation over bluetooth for unmanned air vehicles, in: Proceedings of the 2006 IEEE International Conference on Robotics and Automatio, Orlando, 2006.
[87] G.M.D. Santana, R.S. de Cristo, K.R.L.J.C. Branco, Integrating cognitive radio with unmanned aerial vehicles: an overview, Sensors (Switzerland) 21 (2021), https://doi.org/10.3390/s21030830.
[88] L. Yut, Q. Fei, Q. Geng, Combining Zigbee and inertial sensors for quadrotor UAV indoor localization, in: IEEE International Conference on Control and Automation, ICCA, 2013, https://doi.org/10.1109/ICCA.2013.6565087.
[89] H. Jiao, H. Liu, Z. Wang, Reconfigurable intelligent surfaces aided wireless communication: Key technologies and challenges, in: 2022 International Wireless Communications and Mobile Computing, IWCMC 2022, 2022, https://doi.org/10.1109/IWCMC55113.2022.9824117.
[90] B. Ismaiel, M. Abolhasan, D. Smith, W. Ni, D. Franklin, A survey and comparison of device-to-device architecture using LTE unlicensed band, in: IEEE Vehicular Technology Conference, 2017, https://doi.org/10.1109/VTCSpring.2017.8108256.
[91] Y. Wu, W. Guo, H. Yuan, L. Li, S. Wang, X. Chu, J. Zhang, Device-to-device meets LTE-unlicensed, IEEE Commun. Mag. 54 (2016), https://doi.org/10.1109/MCOM.2016.7470950.
[92] L.M.S. Bine, A. Boukerche, L.B. Ruiz, A.A.F. Loureiro, Leveraging urban computing with the internet of drones, IEEE Internet Things Mag. 5 (2022), https://doi.org/10.1109/iotm.003.2100091.
[93] L.M.S. Bine, A. Boukerche, L.B. Ruiz, A.A.F. Loureiro, Internet of drones and terrestrial networks: a successful partnership, IEEE Internet Things Mag. 6 (2023), https://doi.org/10.1109/IOTM.001.2200265.
[94] L. Abualigah, A. Diabat, P. Sumari, A.H. Gandomi, Applications, deployments, and integration of internet of drones (IoD): a review, IEEE Sensors J. 21 (2021), https://doi.org/10.1109/JSEN.2021.3114266.
[95] J.V. Shirabayashi, L.B. Ruiz, Toward UAV path planning problem optimization considering the internet of drones, IEEE Access 11 (2023), https://doi.org/10.1109/ACCESS.2023.3339227.
[96] G. Grieco, G. Iacovelli, P. Boccadoro, L.A. Grieco, Internet of drones simulator: design, implementation, and performance evaluation, IEEE Internet Things J. 10 (2023), https://doi.org/10.1109/JIOT.2022.3207324.
[97] H.A. Alharbi, B.A. Yosuf, M. Aldossary, J. Almutairi, J.M.H. Elmirghani, Energy efficient UAV-based service offloading over cloud-fog architectures, IEEE Access 10 (2022), https://doi.org/10.1109/ACCESS.2022.3201112.
[98] W. Yang, S. Wang, X. Yin, X. Wang, J. Hu, A review on security issues and solutions of the internet of drones, IEEE Open J. Comput. Soc. 3 (2022), https://doi.org/10.1109/OJCS.2022.3183003.
[99] B.J. Perry, Y. Guo, R. Atadero, J.W. van de Lindt, Unmanned aerial vehicle (UAV)-enabled bridge inspection framework, in: Bridge Maintenance, Safety, Management, Life-Cycle Sustainability and Innovations - Proceedings of the 10th International Conference on Bridge Maintenance, Safety and Management, IABMAS 2020, 2021, https://doi.org/10.1201/9780429279119-17.
[100] E. Belcore, V. Di Pietra, N. Grasso, M. Piras, F. Tondolo, P. Savino, D.R. Polania, A. Osello, Towards a FOSS automatic classification of defects for bridges structural health monitoring, in: Communications in Computer and Information Science, 2022, https://doi.org/10.1007/978-3-030-94426-1_22.
[101] E. Jeong, J. Seo, P.E.J. Wacker, UAV-aided bridge inspection protocol through machine learning with improved visibility images, Expert Syst. Appl. 197 (2022), https://doi.org/10.1016/j.eswa.2022.116791.
[102] X. Yang, E. del Rey Castillo, Y. Zou, L. Wotherspoon, UAV-deployed deep learning network for real-time multi-class damage detection using model quantization techniques, Autom. Constr. 159 (2024), https://doi.org/10.1016/j.autcon.2023.105254.
[103] S. Jiang, Y. Cheng, J. Zhang, Vision-guided unmanned aerial system for rapid multiple-type damage detection and localization, Struct. Health Monit. 22 (2023) 319–337, https://doi.org/10.1177/14759217221084878.
[104] X. Yang, E. del Rey Castillo, Y. Zou, L. Wotherspoon, UAV-deployed deep learning network for real-time multi-class damage detection using model quantization techniques, Autom. Constr. 159 (2024), https://doi.org/10.1016/j.autcon.2023.105254.
[105] T. Omar, M.L. Nehdi, Remote sensing of concrete bridge decks using unmanned aerial vehicle infrared thermography, Autom. Constr. 83 (2017), https://doi.org/10.1016/j.autcon.2017.06.024.
[106] Y. Li, C. Liu, Applications of multirotor drone technologies in construction management, Int. J. Constr. Manag. 19 (2019), https://doi.org/10.1080/15623599.2018.1452101.
[107] L. Duque, J. Seo, J. Wacker, Bridge deterioration quantification protocol using UAV, J. Bridg. Eng. 23 (2018), https://doi.org/10.1061/(asce)be.1943-5592.0001289.
[108] F. Potenza, C. Rinaldi, E. Ottaviano, V. Gattulli, A robotics and computer-aided procedure for defect evaluation in bridge inspection, J. Civ. Struct. Heal. Monit. 10 (2020), https://doi.org/10.1007/s13349-020-00395-3.
[109] A. Mirzazade, C. Popescu, J. Gonzalez-Libreros, T. Blanksvärd, B. Täljsten, G. Sas, Semi-autonomous inspection for concrete structures using digital models and a hybrid approach based on deep learning and photogrammetry, J. Civ. Struct. Heal. Monit. 13 (2023) 1633–1652, https://doi.org/10.1007/s13349-023-00680-x.
[110] T. Xu, Y. Wu, Y. Qin, S. Long, Z. Yang, F. Guo, Automatic steel girder inspection system for high-speed railway bridge using hybrid learning framework, Comput. Aid. Civ. Infrastruct. Eng. (2025), https://doi.org/10.1111/mice.13409 n/a (n.d.).
[111] A. Khaloo, D. Lattanzi, K. Cunningham, R. Dell'Andrea, M. Riley, Unmanned aerial vehicle inspection of the Placer River Trail Bridge through image-based 3D modelling, Struct. Infrastruct. Eng. 14 (2018), https://doi.org/10.1080/15732479.2017.1330891.
[112] H. Kim, Y. Narazaki, B.F. Spencer, Automated bridge component recognition using close-range images from unmanned aerial vehicles, Eng. Struct. 274 (2023), https://doi.org/10.1016/j.engstruct.2022.115184.
[113] Y.M. Mohammed, N. Uddin, C. Tan, Z. Shi, Portable bridge weigh-in-motion (P-B-WIM), in: 9th International Conference on Structural Health Monitoring of Intelligent Infrastructure: Transferring Research into Practice, SHMII 2019 - Conference Proceedings, 2019.
[114] P.J. Sanchez-Cuevas, G. Heredia, A. Ollero, Multirotor UAS for bridge inspection by contact using the ceiling effect, in: 2017 International Conference on Unmanned Aircraft Systems, ICUAS 2017, 2017, https://doi.org/10.1109/ICUAS.2017.7991412.
[115] P.J. Sanchez-Cuevas, P. Ramon-Soria, B. Arrue, A. Ollero, G. Heredia, Robotic system for inspection by contact of bridge beams using UAVs, Sensors (Switzerland) 19 (2019), https://doi.org/10.3390/s19020305.
[116] Y.M. Mohammed, C. Tan, N. Uddin, Fly-by Bridge Inspection using UAVs (standalone portable system), in: Life-Cycle Civil Engineering: Innovation, Theory and Practice - Proceedings of the 7th International Symposium on Life-Cycle Civil Engineering, IALCCE 2020, 2020, https://doi.org/10.1201/9780429343292-93.
[117] X. Jian, Z. Lai, K. Bacsa, Y. Fu, C.G. Koh, L. Sun, A. Wieser, E. Chatzi, A robotic automated solution for operational modal analysis of bridges with high-resolution mode shape recovery, J. Struct. Eng. 150 (2024) 4024081, https://doi.org/10.1061/JSENDH.STENG-12635.
[118] J.N. Satme, R. Yount, J. Vaught, J. Smith, A.R.J. Downey, Modal analysis using a UAV-deployable wireless sensor network, in: Conference Proceedings of the Society for Experimental Mechanics Series, 2024, https://doi.org/10.1007/978-3-031-34942-3_8.
[119] S. Carroll, M. Kalaitzakis, N. Vitzilaios, UAS sensor deployment and retrieval to the underside of structures, in: 2021 International Conference on Unmanned

Aircraft Systems, ICUAS 2021, 2021, https://doi.org/10.1109/ICUAS51884.2021.9476737.
[120] Z. Zhang, A flexible new technique for camera calibration, IEEE Trans. Pattern Anal. Mach. Intell. 22 (2000), https://doi.org/10.1109/34.888718.
[121] C. Harris, M. Stephens, A combined corner and edge detector, in: Proceedings of the Alvey Vision Conference, 2013, https://doi.org/10.5244/c.2.23.
[122] S. Leutenegger, M. Chli, R.Y. Siegwart, BRISK: Binary Robust invariant scalable keypoints, in: Proceedings of the IEEE International Conference on Computer Vision, 2011, https://doi.org/10.1109/ICCV.2011.6126542.
[123] S. Garrido-Jurado, R. Muñoz-Salinas, F.J. Madrid-Cuevas, M.J. Marín-Jiménez, Automatic generation and detection of highly reliable fiducial markers under occlusion, Pattern Recogn. 47 (2014), https://doi.org/10.1016/j.patcog.2014.01.005.
[124] Z. Wu, G. Chen, Q. Ding, B. Yuan, X. Yang, Three-dimensional reconstruction-based vibration measurement of bridge model using uavs, Appl. Sci. (Switzerland) 11 (2021), https://doi.org/10.3390/app11115111.
[125] T. Khuc, T.A. Nguyen, H. Dao, F.N. Catbas, Swaying displacement measurement for structural monitoring using computer vision and an unmanned aerial vehicle, Measurement (Lond) 159 (2020), https://doi.org/10.1016/j.measurement.2020.107769.
[126] G.H. James III, T.G. Carne, J.P. Lauffer, J.P. Lauffer, The natural excitation technique (NExT) for modal parameter extraction from operating wind turbines, Int. J. Anal. Exp. Mod. Anal. 10 (1993).
[127] S.H. Sim, B.F. Spencer, M. Zhang, H. Xie, Automated decentralized modal analysis using smart sensors, Struct. Control. Health Monit. 17 (2010), https://doi.org/10.1002/stc.348.
[128] K. Hacıefendioğlu, V. Kahya, M.G. Limongelli, F.Y. Okur, A.C. Altunışık, T. Aslan, S. Pembeoğlu, C. Duman, A. Bostan, H. Aleit, Applications of optical flow methods and computer vision in structural health monitoring for enhanced modal identification, Structures 69 (2024) 107414, https://doi.org/10.1016/j.istruc.2024.107414.
[129] Y. Han, G. Wu, D. Feng, Vision-based displacement measurement using an unmanned aerial vehicle, Struct. Control. Health Monit. (2022), https://doi.org/10.1002/stc.3025.
[130] Z. Yan, Z. Jin, S. Teng, G. Chen, D. Bassir, Measurement of bridge vibration by UAVs combined with CNN and KLT optical-flow method, Appl. Sci. (Switzerland) 12 (2022), https://doi.org/10.3390/app12105181.
[131] Y. Bai, H. Sezen, A. Yilmaz, R. Qin, Bridge vibration measurements using different camera placements and techniques of computer vision and deep learning, Adv. Bridge Eng. 4 (2023), https://doi.org/10.1186/s43251-023-00105-1.
[132] D. Marchisotti, E. Zappa, Feasibility of drone-based modal analysis using ToF-grayscale and tracking cameras, IEEE Trans. Instrum. Meas. 72 (2023), https://doi.org/10.1109/TIM.2023.3281628.
[133] D. Lydon, M. Lydon, S. Taylor, J.M. Del Rincon, D. Hester, J. Brownjohn, Development and field testing of a vision-based displacement system using a low cost wireless action camera, Mech. Syst. Signal Process. 121 (2019), https://doi.org/10.1016/j.ymssp.2018.11.015.
[134] G. Michel Guzman-Acevedo, J.A. Quintana-Rodriguez, G. Esteban Vazquez-Becerra, J. Garcia-Armenta, A reliable methodology to estimate cable tension force in cable-stayed bridges using unmanned aerial vehicle (UAV), Measurement 229 (2024) 114498, https://doi.org/10.1016/J.MEASUREMENT.2024.114498.
[135] S. Marcellini, S. D'Angelo, A. De Crescenzo, M. Marolla, V. Lippiello, B. Siciliano, Development of a semi-autonomous framework for NDT inspection with a tilting aerial platform, 2024. https://arxiv.org/abs/2407.03003.
[136] M. Zhou, Z. An, N.Y. Chong, Wall-sticking drone for non-destructive inspection of oblique planes, in: 2024 IEEE International Conference on Mechatronics and Automation (ICMA), 2024, pp. 1741–1746, https://doi.org/10.1109/ICMA61710.2024.10632995.
[137] R.A. Mattar, R. Kalai, Development of a wall-sticking drone for non-destructive ultrasonic and corrosion testing, Drones 2 (2018), https://doi.org/10.3390/drones2010008.
[138] D. Robert, Aerial robots for contact-based ultrasonic thickness measurements for field inspections, Mater. Eval. 79 (2021), https://doi.org/10.32548/2021.me-04213.
[139] M. Schewe, M.A.A. Ismail, R. Zimmermann, U. Durak, C. Rembe, Flyable Mirror: Airborne laser Doppler vibrometer for large engineering structures, in: J Phys Conf Ser, 2024, https://doi.org/10.1088/1742-6596/2698/1/012007.
[140] S. Ri, J. Ye, N. Toyama, N. Ogura, Drone-based displacement measurement of infrastructures utilizing phase information, Nat. Commun. 15 (2024), https://doi.org/10.1038/s41467-023-44649-2.
[141] S. Zhuge, X. Xu, L. Zhong, S. Gan, B. Lin, X. Yang, X. Zhang, Noncontact deflection measurement for bridge through a multi-UAVs system, Comput. Aided Civ. Inf. Eng. 37 (2022), https://doi.org/10.1111/mice.12771.
[142] F. Jalinoos, M. Amjadian, A.K. Agrawal, C. Brooks, D. Banach, Experimental evaluation of unmanned aerial system for measuring bridge movement, J. Bridg. Eng. 25 (2020), https://doi.org/10.1061/(asce)be.1943-5592.0001508.
[143] K. Kumarapu, S. Mesapam, V.R. Keesara, A.K. Shukla, N.V.S.K. Manapragada, B. Javed, RCC structural deformation and damage quantification using unmanned aerial vehicle image correlation technique, Appl. Sci. (Switzerland) 12 (2022), https://doi.org/10.3390/app12136574.
[144] Z. Yan, Z. Jin, S. Teng, G. Chen, D. Bassir, Measurement of bridge vibration by UAVs combined with CNN and KLT optical-flow method, Appl. Sci. (Switzerland) 12 (2022), https://doi.org/10.3390/app12105181.
[145] R.E. Kalman, A new approach to linear filtering and prediction problems, J. Fluids Eng. Trans. ASME 82 (1960), https://doi.org/10.1115/1.3662552.
[146] T. Pfeifer, P. Weissig, S. Lange, P. Protzel, Robust factor graph optimization - A comparison for sensor fusion applications, in: IEEE International Conference on Emerging Technologies and Factory Automation, ETFA, 2016, https://doi.org/10.1109/ETFA.2016.7733598.
[147] L. Zhuang, X. Zhong, L. Xu, C. Tian, W. Yu, Visual SLAM for unmanned aerial vehicles: localization and perception, Sensors 24 (2024), https://doi.org/10.3390/s24102980.
[148] B. Zhao, Y. Huang, H. Wei, X. Hu, Ego-motion estimation using recurrent convolutional neural networks through optical flow learning, Electronics (Switzerland) 10 (2021), https://doi.org/10.3390/electronics10030222.
[149] P.F. Giordano, C. Iacovino, S. Quqa, M.P. Limongelli, The value of seismic structural health monitoring for post-earthquake building evacuation, Bull. Earthq. Eng. 20 (2022), https://doi.org/10.1007/s10518-022-01375-2.