remote sensing

Review

Remote Sensing in Bridge Digitalization: A Review

Joan R. Casas [1,*], Rolando Chacón [1], Necati Catbas [2], Belén Riveiro [3] and Daniel Tonelli [4]

[1] Department of Civil and Environmental Engineering, UPC-BarcelonaTech, 08034 Barcelona, Spain; rolando.chacon@upc.edu
[2] Department of Civil, Environmental and Construction Engineering, University of Central Florida, Orlando, FL 32816, USA; catbas@ucf.edu
[3] CINTECX, GeoTECH Group, Campus Universitario de Vigo, Universidade de Vigo, As Lagoas, Marcosende, 36310 Vigo, Spain; belenriveiro@uvigo.gal
[4] Department of Civil, Environmental and Mechanical Engineering, University of Trento, 38123 Trento, Italy; daniel.tonelli@unitn.it
* Correspondence: joan.ramon.casas@upc.edu

Abstract: A review of the application of remote sensing technologies in the SHM and management of existing bridges is presented, showing their capabilities and advantages, as well as the main drawbacks when specifically applied to bridge assets. The main sensing technologies used as corresponding platforms are discussed. This is complemented by the presentation of five case studies emphasizing the wide field of application in several bridge typologies and the justification for the selection of the optimal techniques depending on the objectives of the monitoring and assessment of a particular bridge. The review shows the potentiality of remote sensing technologies in the decision-making process regarding optimal interventions in bridge management. The data gathered by them are the mandatory precursors for determining the relevant performance indicators needed for the quality control of these important infrastructure assets.

Keywords: bridges; digitalization; SHM; BIM; digital twin; management; sensors; platforms

check for updates

Citation: Casas, J.R.; Chacón, R.; Catbas, N.; Riveiro, B.; Tonelli, D. Remote Sensing in Bridge Digitalization: A Review. *Remote Sens.* **2024**, *16*, 4438. https://doi.org/10.3390/rs16234438

Academic Editors: Jorge Delgado García and Wen Liu

Received: 28 August 2024
Revised: 4 October 2024
Accepted: 18 October 2024
Published: 27 November 2024

1. Introduction

Bridges are a vital component of the transportation infrastructure, providing a means for people and goods to travel across bodies of water, valleys, and other obstacles. Due to the time of construction, many of the world's bridges are aging and deteriorating, and maintaining them is becoming a significant challenge for transportation departments around the globe. With budgets constrained and resources limited, optimizing bridge maintenance has become an increasingly important issue.

The use of digital assistants for maintenance plans, such as digital twins, is said to be a substantial improvement in the maintenance sector in the years to come [1–4]. A digital twin is a living virtual model of a real-world object, and it can be used to track the behavior and performance of that object at the right time. In the case of bridges, digital twins can be used to create an accessible living model of the bridge to which updated data collected from its physical counterpart can be added in various forms. The information model includes data related to its design, construction, and current condition.

By using digital twins as comprehensive interfaces, agencies and transportation departments can optimize bridge maintenance in several ways. First, the digital replica is the main part of the inventory of the physical asset, so it mainly contains all the geometrical and mechanical definitions of its members, as well as the interventions done in the bridge since its opening to the traffic (for instance, the result of the loading test can be included) until now. Second, they can use the digital twin to monitor the condition of the bridge in a timely manner. This allows engineers to identify potential problems before they become serious and to schedule maintenance and repairs accordingly. Additionally, digital twins can be used to simulate the effects of different maintenance strategies, allowing engineers to determine which approach will be most effective in extending the life of the bridge.

On the other hand, remote sensing (RS) refers to the technique of gathering information about an object or a phenomenon without coming into direct physical contact with it. This is typically accomplished through the use of sensors and instruments that are designed to collect data from a distance, often from a fixed point, terrestrial vehicles, aircraft or satellites in orbit around the Earth. Remote sensing acquires characteristics of an asset by measuring properties by means of reflected and emitted radiations from a distance. This principle has been understood from many measuring perspectives. Laser, acoustic, thermal, or optic emissions allow for the collection of a wide variety of physical characteristics.

Remote sensing can be used to gather a wide range of information, including information about the physical characteristics of the asset, such as geometry, topography, movements of the asset, land cover, or vegetation, as well as information about atmospheric conditions, weather patterns, hydraulic patterns or ocean currents. The data collected through remote sensing is typically analyzed using specialized software and algorithms to extract information and insights that can be used for a variety of purposes, including environmental monitoring, resource management, and disaster response.

Remote sensing data such as satellite imagery and LiDAR scans can add extremely valuable data. For the former, space-borne trends on weather, currents, or land can be gathered. For the latter, highly detailed 3D models of bridges can then be generated and leveraged within its digital twins.

Due to the important capabilities of such a monitoring system, remote sensing has been applied to many different engineering fields and environments. A comprehensive review of all applications up to now would be a huge amount of work and material that will not be possible to summarize in just one paper. Therefore, intentionally, the review content of the present paper is only focused on bridges. Despite the huge applications of remote sensing for bridges presented in the last decades, most research applications are highly disaggregated, attending to the specific technology applied. This means that most of the published works and reviews are focused on a specific technology and the research community working in that specific domain. However, a transversal view of the wide variety of remote sensing techniques that can be used for bridge digitalization and monitoring has not yet been addressed. Thus, this review paper aims to bridge this gap and provide a harmonized vision of the various remote technologies applied to the digitalization of existing bridges and guide readers in the understanding of the potential applications and capabilities of the different remote sensing techniques to assist decision-making process related to their preventive maintenance of bridges. This also includes guidance in the appropriate post-processing techniques for each particular dataset, with the objective of a minimum life-cycle cost and, thus increased sustainability. The objective is not just to look into the characteristics of the digital data that can be gathered with RS but on how the appropriate post-processing of this raw data allows the calculation of the so-called Key Performance Indicators (KPI) that are the basis of practical decisions concerning bridge safety and serviceability when compared to pre-defined thresholds [5–7]. To this end, the paper also helps bridge the gap between academic research and professional application by looking at the new possibilities provided by advanced technologies such as RS. For this reason, this paper is oriented towards an end-user approach, and, therefore, the different remote sensing techniques are described based on real-world applications in existing bridges.

Accounting for a wide interpretation of the concept of RS, the review includes all contactless sensing technologies. Disaggregated data are often referred to as "data silos". Understanding the nature of this data is paramount for subsequent integration within vaster information constructs such as Digital Twins (DT). The road to digitalization shows "data bottlenecks" that the industry needs to overcome in the following years. It presumes that a consistent understanding of the nature of the data in the generation of new interfaces. Remote sensing techniques are particularly different in terms of data structures and their nature, and it is worth summarizing these needs in the world of bridge engineering in a document for further reference.

2. Relevant Technologies for Bridge Engineering

Remote sensing techniques such as laser scanning, radar, GPS, satellites, imagery, and thermography can provide detailed data on everything from deformation and displacement to stress and strain. This information allows engineers and maintenance crews to identify potential problems and make targeted interventions, helping to extend the life of bridges and keep them safe for public use. A detailed literature revision of these techniques is provided in this chapter. As mentioned before, the objective is not a comprehensive review based on a full scanning and bibliometric analysis of all relevant literature on the subject of remote sensing but just a review of the main applications in the specific area of bridge engineering. This is complemented in Section 3 by the explanation of several case studies where the authors have been involved. Based on their experiences and background, the presented case studies show how remote sensing measurements can be transferred into digital models and bridge performances, which are the basis for further decision-making in bridge management. The main conclusions of the review are outlined in Section 4.

2.1. Instruments and Techniques

2.1.1. Laser Scanning

Laser scanners are surveying instruments that combine distance and angle measurements to determine 3D point coordinates.

Static scanners, also known as terrestrial laser scanners (TLS), were the first technology used in terrestrial environments, where civil engineering was one of the fields where this technology demonstrated more applicability. A dense point cloud is generated in a spherical coordinate system. Most scanners automatically convert the spherical coordinates into Cartesian coordinates (X, Y, Z) for each point.

The increasing demand for the digitalization of extensive terrestrial infrastructures such as roads and railway networks within a reasonable timeframe promoted the development of more efficient data collection systems [8]. Thus, mobile laser scanning systems became a popular technology for the inspection and monitoring of large transport infrastructure, where bridges are among the most common critical assets linked to these infrastructure networks. Differently from static systems, mobile laser scanning systems employ two observation modes: (i) formerly, the stop-and-go mode, which is a hybrid solution between static instruments mounted in mobile platforms; and (ii) the on-the-fly mode, where the imaging sensors for distance measurement using LiDAR are the same, but the laser beam is only deflected within one plane. This results in a point cloud created according to a cylindrical coordinate system, where the third dimension is obtained with the motion of the vehicle by accessing the trajectory data.

In [9], when laser scanning was still a young technique, the authors already foresaw its impact as a 3D measuring technique for many different applications. Later, Riveiro and Lindenberg [10] revised the advances suffered by laser scanning in the last decade, where bridges were among the most remarkable applications. Recently, Rashidi et al. [11] published a revision of the use of terrestrial laser scanning in bridge monitoring. In fact, it seems clear that when focusing on the applications to civil engineering, terrestrial laser scanning technologies (both static and mobile) have changed the vision of how to conduct condition surveys of existing infrastructure assets. This technology noticeably impacted the modeling and inspection of existing bridges due to its ability to massively, accurately, and efficiently collect 3D geometry data.

The first works about laser scanning in bridge engineering presented processing flows using commercial software packages, typically linked to specific laser scanner manufacturers. Additionally, manual processing was the predominant trend for the data analysis. In these works, the workflow was quite straightforward, and authors typically conducted some common operations comprising scan registration, point cloud cleansing and homogenization, meshing and even coloring using complementary photogrammetric surveys, among others [12,13]. One of the pioneer applications of terrestrial laser scanning for bridges was deformation monitoring. Thus, one of the most remarkable works was published by Gordon et al. [14], where the successful deformation monitoring of bridge structural members was not the only contribution. In addition, they demonstrated that TLS systems can provide up to 12 times better accuracy in the measurement of deflections than the nominal accuracy of the instrument for single-point measurements. Later, Zogg and Ingensand [15] incorporated terrestrial laser scanning into the deflection monitoring of a viaduct, alongside traditional surveying methods, to validate its effectiveness for such purposes. Likewise, Berényi et al. [16] conducted research to validate the application of TLS in load test measurements on bridges. Their paper delves into various aspects, including the approach to measuring complex structures with limited accessibility. Many works started proposing combined surveys, including both traditional leveling and terrestrial laser scanning during load tests (e.g., [17]), because even though TLS cannot replace high-accurate geodetic measurements, the 3D surface measurement results are very valuable in monitoring the deformations in a continuous domain [18]. Alamdari et al. [19] compared laser scanning data to other accurate geodetic methods in load tests of a cable-stayed bridge. The data was very useful in validating the deformations predicted by the FEM model of the bridge. Recently, Truong-Hong et al. [20] presented an interesting analysis of the main sources of errors in the deformation monitoring of structural members: (i) error produced due to registration of multiple scanning stations; (ii) error committed during the segmentation of point clouds of structure surfaces; (iii) definition of the surface of reference; and (iv) influence of noisy points (outlier and/or mixed pixels).

Another frequent application of laser scanning in bridge evaluation deals with the creation of geometric models that can be later converted to structural models for further safety analysis. For example, Riveiro et al. [21] introduced models that enable the structural analysis of arch bridges using the rigid blocks method. Later, Walsh et al. [22] presented methodologies for segmenting point clouds of various structural components, utilizing both laboratory specimens and real bridge testing. Conde-Carnero et al. [23] presented the workflow for the creation of structural models in two bridge typologies. The structural assessment of steel bridges from TLS point cloud data was also addressed by Gyetvai et al. [24]. In their work, the authors proposed a non-parametric regression and kernel density estimation techniques were utilized to determine the bridge dimensions and semantically segment the point clouds into web and flange points. From these outputs, the numerical model could be created. In a recent work, Trias et al. [25] quantified the errors in the flexural capacity of bridges when using LiDAR point clouds collected during operational conditions. They found that when they directly extracted measurements from the point cloud, the error in flexural capacity was between 9 and 13%. If the measurements are estimated using plane fitting, the errors in flexural capacity are reduced to between 4–7%.

In the creation of structural models from laser scanning data, it is common to integrate the scanning data with other non-destructive data to assess not only the external geometry but also internal properties very relevant to the structural response. Several works investigating the structural assessment of ancient stone arch bridges combine laser scanning and Ground Penetrating Radar (GPR) to create the geometric model and advanced numerical modeling to conduct the structural assessment [26,27]. Other recent works also combine laser scanning data with other NDT techniques, such as Operational Modal Analysis (OMA) of sonic tests, to not only create the basic computational model but also allow model updating using the experimental data or deformation maps created from the dense point cloud [28,29].

In continuation of these last works, Structural Health Monitoring (SHM) has become another popular application, and laser scanning has proved to be very effective. There is a vast body of literature reporting works dealing with the detection of cracks, monitoring deformation, and automated detection of defects and changes in the structure over time. These applications showed an increasing trend in the last decade in connection to automation in data processing, which has been probably the most important research line in laser scanning for bridge engineering. As recently reported in a review article by Kaartinen et al. [30], the contributions in terms of damage detection and characterization are relevant. Some of the most direct applications using 3D dense point clouds are crack detection, which was successfully reported for concrete bridges [31], masonry walls [32] or timber beams [33].

Point clouds are unorganized sets of points without any information on the object to which a point belongs, so preliminary operations are needed not only to add semantics to the points but also to cluster them into subsets to relate them to real structural components. In addition, topology information is also essential when structural damages are to be analyzed because the spatial relationship between structural elements is a key aspect to consider when analyzing the structural performance of the bridge as a whole. Thus, one common task in automated SHM from laser scanning data typically involves one preliminary operation consisting of the semantic and instance segmentation of the point clouds. In this sense, relevant work has been presented for the automated inspection of masonry arch bridges. A heuristic method was presented by Riveiro et al. [34], where the global point cloud of bridges was fully automatically segmented into instances corresponding to spandrel walls, arches, piers, abutments, parapets and pathways. Recently, the use of deep neural networks (BridgeNet) was proved to efficiently provide semantic segmentation for this same bridge typology [35]. Semantic segmentation of reinforced concrete bridge elements was also reported in the literature [36].

After the instances are identified, their composing points can be analyzed further to detect some of the damages mentioned above, as reported by Kim et al. [37] in the case of concrete bridges, or to proceed with further geometric analysis. For example, in relation to this last trend, Sánchez-Rodríguez et al. [38] presented an approach for fully automated inspection of piers in masonry arch bridges. The analysis of out-of-plane deformations in masonry arch bridges (spandrel walls and arches) was presented by the same authors in a masonry arch bridge in Portugal [28].

Steel truss-type bridges were also subjected to fully automated geometric reconstruction using laser scanning data. The complementary work recently presented by Lamas et al. [39] and Justo et al. [40] proposed a pipeline for laser scanning data processing consisting of a heuristic semantic and instance segmentation of truss bars for further geometric modeling and exportation using IFC-compliant models. These scan-to-BIM approaches will be presented further in the case studies presented in Section 3 of this paper.

In cable-based structural systems, such as suspension bridges, cable nets, or cable-stayed structures, the accurate determination of forces in the elements is critical for ensuring structural integrity and safety. When the geometry of these systems is scanned using laser-based remote sensing techniques such as LiDAR or 3D laser scanning, the resulting data provides a highly detailed representation of the deformed or current geometry of the cables and other components. However, the challenge lies in translating this geometric data into meaningful structural forces, which requires a process known as mechanical inversion. Mechanical inversion is essential because the forces within the elements of cable-based structures are not directly measurable from geometric data alone. Cables, by nature, are highly flexible, and their shapes are governed by the forces acting upon them, including tension, self-weight, and external loads. By utilizing mechanical inversion, the scanned geometric data can be used to reverse-engineer the force distribution within the system [41,42].

2.1.2. Radar

Radio Detection and Ranging (RADAR) systems work by transmitting an electromagnetic signal from a transmitter through an antenna and into space. When the signal hits an object, it bounces back and creates an echo signal, which is detected by the antenna and processed by a receiver. The receiver filters out noise and sends the signal to a threshold decision system, which produces useful data. The system calculates the range of the object by measuring the time it takes for the signal to bounce back and determines the object's location by calculating the angle between the direction of the echo signal and the antenna's direction. For moving objects, the Doppler effect is used to calculate both the object's speed and range. Although there are different types of RADAR systems, they all use this basic working principle to detect and locate objects in a variety of applications.

When it comes to the maintenance of assets within the built environment, such as bridges, specific radar technologies are used [43].

The interferometric radar is a very good tool for remote measurements of dynamic displacements when contact displacement sensors are difficult to deploy (bridges with high-level decks, crossing rivers, highways, or railways [44,45].

This discussion will focus exclusively on these technologies, which include space-borne synthetic Aperture Radar (SB-SAR) and ground-based synthetic Aperture Radar (GB-SAR).

Space-Borne Synthetic Aperture Radar

The applications of SB-SAR are vast and varied. Earth-observing satellites equipped with imaging sensors that operate in different spectral areas, such as optical, infrared, and radio waves, are currently used for space-borne remote sensing. Optical and infrared sensors are highly sensitive to weather conditions and work only during daylight hours. In contrast, radio waves are robust and can operate even in poor weather conditions. SB-SAR is a remote sensing method that combines the return echoes of radar pulses emitted from a rapidly moving observation platform to allow for high-resolution ground surveillance. One significant advantage of using SAR is its coherence, which enables the user to process images from subsequent overflights for interferometric analyses. Interferometric Synthetic Aperture Radar (InSAR) is a geodetic method that uses two or more SAR images to generate maps of surface deformation or digital elevation, which can potentially measure millimeter-scale changes in deformation over days to years.

PS-InSAR (Persistent Scatterer Interferometric Synthetic Aperture Radar) is a remote sensing technique that uses radar data from satellites to monitor ground deformation over time. The radar acts as the sensor on a moving platform. The technique is based on the use of multiple Synthetic Aperture Radar (SAR) images of the same area, which are processed to identify Persistent Scatterers (PS)—stable and reflective features on the ground, such as buildings or rocks that can be detected over time. By analyzing the radar signal from each PS in multiple SAR images, PS-InSAR can detect and measure ground deformation with millimeter-level accuracy. This makes it a valuable tool for monitoring and studying various geohazards, such as landslides, subsidence, and earthquakes, as well as for infrastructure monitoring and urban planning. PS-InSAR has gained ground in recent years due to the availability of SAR data from multiple satellite missions, such as the European Space Agency's (ESA) Sentinel-1 mission.

Observing bridges with PS-InSAR is a difficult task because of their large vibrations—this issue is particularly critical when heavy traffic or strong winds are present.

A summary of recent applications of SAR-based processing methods to the successful evaluation of the structural components of bridges is reported in [46].

Challenges in Data Interpretation and Integration.

Recently, studies have been conducted on the possibility of using high-resolution synthetic aperture radar (SAR) data obtained from satellites to monitor bridge deformations at regular intervals without the need for any equipment to be installed on the bridge. Satellite-based InSAR technologies are effectively reaching proper use to monitor bridge deformations with millimeter precision over the long term.

However, interpreting InSAR data and integrating it with civil infrastructure data can be challenging. The study on the Oglio River Bridge in Italy [47] illustrated these challenges, especially when comparing InSAR data with GNSS measurements. The study found discrepancies in displacement magnitudes measured by those technologies, pointing toward potential difficulties in using satellite-based methods for precise structural health monitoring. Additionally, the Colle Isarco Viaduct research [48] tackled phase-unwrapping issues in bridge sections characterized by significant displacements, a common problem for long-span bridges. The study suggests a possibility of overcoming this issue through data fusion with other monitoring techniques, e.g., topographic systems or GNSS.

Of particular interest is the paper [49] from Milillo et al., where the authors report how the generation of a displacement map for the Polcevera Bridge in Genova from space-based SAR measurements acquired by the Italian constellation COSMO-SkyMed and the European constellation Sentinel-1A/B over the period 2009–2018 revealed that the bridge was undergoing an increased magnitude of deformations over time prior to its collapse. The results have shown that the deck next to the collapsed pier has been characterized since 2015 by increasing relative displacements. The COSMO-SkyMed dataset also revealed the increased deformation magnitude over time of several points located near the strands of this deck between 12th March 2017 and August 2018. However, in a commentary paper by Lanari et al. [50], they found the results from Milillo et al. to be highly questionable. Using the Small BAseline Subset (SBAS) and the Advanced Tomographic SAR (TomoSAR) approaches, respectively, the analysis of Lanari et al. [50] shows that, although both the SBAS and the TomoSAR analyses allow achieving denser coherent pixel maps relevant to the Morandi bridge, nothing of the pre-collapse large displacements reported in Milillo et al. appears in their results, leading to deeply disagree with the findings of their InSAR analysis. This divergence in the analysis of the satellite data is clear evidence that there is still a long way to go before these techniques applied to the monitoring of bridges can be shown as mature enough in the prognosis of bridge failures. Validating the InSAR data against traditional monitoring methods is crucial for its broader acceptance. The Colle Isarco Viaduct case [48] juxtaposed InSAR data with traditional topographic measurements, successfully demonstrating the use of InSAR in monitoring large-scale infrastructure. However, the study also highlighted the need for enhanced data processing techniques, particularly in handling phase ambiguity, to fully leverage InSAR's capabilities for infrastructure monitoring.

Integration of InSAR with Traditional Methods.

Due to the challenges mentioned above, the combination of InSAR with traditional monitoring techniques should be investigated as a solution for this leverage.

Several studies have demonstrated the successful integration of InSAR with traditional monitoring methods. For instance, the research on London's Waterloo Bridge [51] utilized InSAR data alongside automated total station (ATS) systems and on-site sensors. This integration allowed the one-directional limitation of InSAR to be overcome, providing a more comprehensive understanding of the bridge's structural behavior. Similarly, the study by D'Amico et al. [52] combined Ground Penetrating Radar (GPR) with InSAR (COSMO-SkyMed), offering detailed subsurface information along with broader structural stability insights in the analysis of steel truss bridge. This holistic approach allowed for a more nuanced understanding of the bridge's condition, especially in bridge-infrastructure transition areas.

Recently, within the 2019–2021 DPC-ReLUIS Project, an experimental program was conducted in Italy that combined information obtained from both satellite data and on-site vibrational measurements. The test site selected for this study was the "Ponte della Musica—Armando Trovajoli" bridge, as described in the work of Ponzo et al. [53]. The researchers utilized extended sequences of satellite Synthetic Aperture Radar (SAR) acquisitions, gathered from both ascending and descending orbits by the Italian COSMO-Skymed (CSK) constellation, covering a wide urban area in Rome (Figure 1). The data obtained were analyzed using GIS software and were classified according to structural requirements. Within the same project, bridge horizontal and vertical displacements obtained from InSAR were compared with measurements from GNSS receivers and on-site topographic systems [47,48]. In the first case, the bridge (Isola Dovarese bridge) is a standard short-span bridge, and the comparison results using PS-InSAR were very disappointing, with significant inaccuracies in the comparisons. However, the second case's results involving a long-span viaduct also with high piers (Colle Isarco viaduct) show the limitations of accurately measuring displacements higher than half the wavelength (λ/2) of the radar signal given by phase ambiguity in the bridge with long spans and high piers.

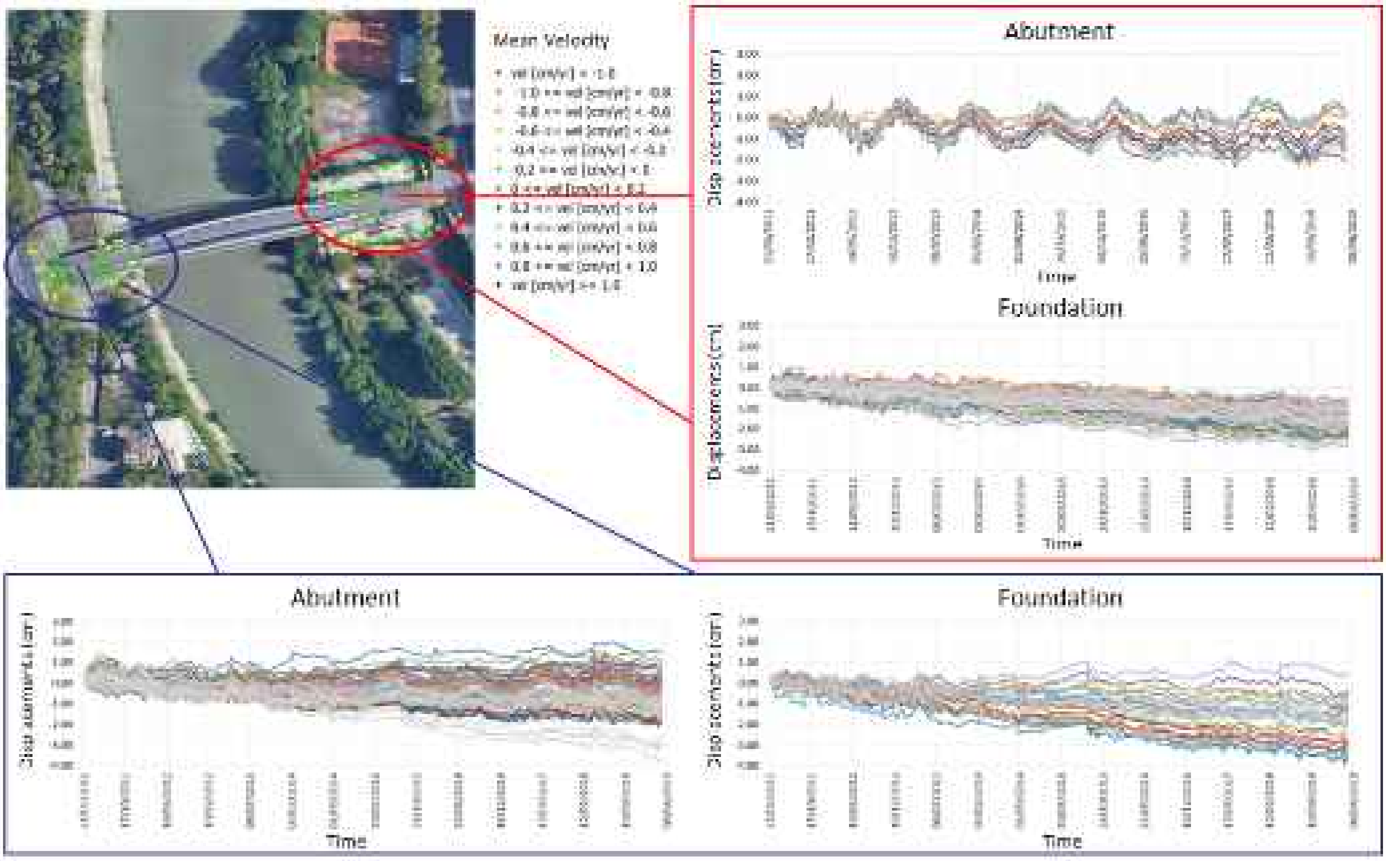


Figure 1. Time series for displacements, ascending orbit. Different color lines refer to different PSs [53].

While SAR has many advantages, it is unlikely that it can entirely replace traditional monitoring systems in the near future. It is more likely that InSAR complements them, offering a way to track displacement on a network level, while traditional monitoring is used only when it is needed the most. Specifically, traditional monitoring provides direct measurements of interest and high-quality imagery, allowing engineers easier structural health interpretation and surface damage detection of cracks or other visible signs of structural deterioration, which SAR cannot detect directly. InSAR allows for the detection of deformation over large areas, even under extreme weather conditions and in areas hard to reach by inspectors, as well as areas where long-term movements are of interest more than short-term responses (scour in bridge piers and movement of abutments). However, SAR images do not provide the same level of detail, sampling frequency, and accuracy as traditional monitoring techniques.

Large-Scale Monitoring and Structural Failure Prevention.

InSAR technology has shown great promise for large-scale monitoring and structural failure prevention. The Rochester Bridge study in the UK [54] utilized InSAR data processed through Persistent Scatterer Interferometry (PSI), combined with unsupervised machine learning clustering techniques [k-means algorithm]. This approach enabled the identification of different deformation sub-areas on the bridge, which is vital for targeted maintenance. The North Channel Bridge study in Ontario, Canada, further validated the efficacy of InSAR in monitoring the structural health of large structures [55]. The research confirmed the accuracy of InSAR data against numerical modeling, demonstrating its potential as a reliable monitoring tool.

The feasibility of using this technique in the analysis and prognosis of bridge collapses is well demonstrated in [56]. The collapse of the Albiano Magra Bridge in Italy on 8 April 2020 demonstrated the effectiveness of the proposed method in supporting forensic engineering assessments and how the failure could have been prevented by a close following of the bridge displacements in the previous three years.

In [57], Qin et al. introduced a multi-temporal Differential Interferometric Synthetic Aperture Radar (DInSAR) method for remotely investigating the deformation characteristics and mechanisms of bridges in Hong Kong. The bridges under study were of a complex nature, including cable-stayed and multi-span arch designs, and a series of points sensitive to damage were identified within these structures. A recent analysis by Xing et al. [58] used Persistent-Scatter Interferometric Synthetic Aperture Radar (PS-InSAR) to derive displacement information from the Hong Kong–Zhuhai–Macao bridge (HZMB), which is located nearby. The authors presented a detailed analysis of the time series data.

Correlation with Environmental Factors and Accuracy.

The evidence of correlation between bridge movements measured by satellite InSAR and environmental factors (e.g., temperature variation) confirms the possibility of using InSAR to monitor bridge distortions over time. The A22 Po River Bridge study in Italy [59] highlighted this possibility, revealing distinct responses of different bridge sections to temperature variations. This study showcased InSAR's ability to measure periodic movements, which closely matched the theoretical thermal expansion coefficients for the bridge's materials. In Canada, the Jacques Cartier and Victoria Bridges study [60] developed an early warning system using InSAR and exploiting this correlation. This system could detect unexpected bridge displacements potentially caused by environmental influences, emphasizing the importance of continuous monitoring for early detection of potential damages. InSAR's ability to detect these movements provides invaluable insights into the bridge's response to environmental stresses. However, the accuracy of InSAR in capturing these movements can be influenced by factors such as the orientation of the bridge relative to the satellite's line of sight (LOS), as noted in the Waterloo Bridge study [51]. This highlights the importance of considering the geometrical relationship between the bridge and the satellite in the planning and interpretation of InSAR data.

In Vienna (Austria), a comprehensive study performed by Schlögl et al. [61] of the Seitenhafen bridge using Sentinel-1 imagery was carried out, also including the atmospheric correction of InSAR measurements using high spatial tropospheric delay maps (GACOS).

Technical bottlenecks and deployment limitations of SAR.

While SAR offers many advantages, there are still technical bottlenecks and limitations that need to be addressed:

- Spatial resolution: SAR images have a resolution on the order of meters, which can limit the detection of movements of small structural elements.
- Temporal resolution: the current revisit time of the many constellations is in the order of days (e.g., COSMO-SkyMed has a revisit time of 16 days and Sentinel-1 of 12 days), which may not be sufficient for monitoring rapidly evolving events affecting a structure.
- Atmospheric interference: Atmospheric conditions can introduce errors in SAR measurements, which need to be carefully modeled and corrected.
- Geometric Distortion: Issues like layover, foreshortening, and shadowing may complicate the interpretation of the data acquired in areas with complex topography (e.g., bridges in mountainous or urban areas).
- Movement directions: InSAR is typically less effective at detecting horizontal displacements than vertical ones. Specifically, for some bridges and structures where lateral movement might be crucial, this can be a limitation.
- Dependence on LOS: InSAR measurements are LOS-dependent, meaning they are most sensitive to movement in the direction of the SAR sensor orientation. This can make detecting certain types of displacement (e.g., along-axis deformation of a bridge)

more difficult unless the satellite's orbital geometry is specifically optimized for the structure being monitored.

Ground-Based Synthetic Aperture Radar

On the other hand, Ground-based SAR interferometry (GBInSAR or TInSAR) is a remote sensing technique that allows for the displacement monitoring of various objects such as slopes, volcanoes, landslides, bridges, and buildings. Similar to satellite SAR interferometry, GBInSAR obtains the synthetic aperture of the radar through an antenna moving on a rail. By emitting and receiving microwave signals, the technique can achieve a high-resolution 2D radar image with high accuracy in displacement measurement. The accuracy of displacement measurement depends on the specific local and atmospheric conditions and the system used. One such system is the IBIS (Image by Interferometric Survey-Structure) developed by IDS and the University of Florence, which is used for static and dynamic monitoring of various structures. In the literature, there are examples of GBInSAR being used for the deformation monitoring of bridge structures. Erdélyi et al. [17] conducted a spatial data analysis using GB-SAR to monitor the deformation of the Liberty Bridge at the Slovakia–Austria border, including an analysis of static and dynamic vibrational data. A two-part study in [62] was conducted to monitor the Liusha Peninsula landslide and Baishazhou Yangtze River Bridge using different techniques, including differential GB SAR, virtual reality-based panoramic technology, and ground-based real aperture radar (GB-RAR). The results were analyzed and compared in both the time and frequency domains. The Nanjing–Dashengguan high-speed railway bridge (NDHRB), located in the Nanjing section of the middle and lower reaches of the Yangtze River in China, was also monitored using GB-SAR by Huang et al. [63]. An IBIS-S sensor was used to study the dynamic behavior of the bridge.

Miccinesi et al. [64] conducted a bridge surveillance operation in Italy utilizing a Multi-Monostatic GB SAR. They utilized a modified version of IBIS-FM MIMO radar, which consisted of four connected antennas. The study also included an experiment that focused on the Varlungo Bridge located in Florence. Pieraccini et al. [44] performed dynamic studies for masonry bridge monitoring using GB-SAR in Iran. The Veresk Bridge, as well as the Kaflan-Kuh Bridge, were analyzed. The equipment was a prototype operating in the Ku-Band. Comprehensive research on bridge monitoring using GB-SAR was presented by Xing et al. [65]. The researchers used a ground-based radar system on a bridge in service crossing the Yangtze River in Wuhan. They also included improved projection methods for computing the deflection of the bridge.

When measuring vibration with GBinSAR, the closer the vibration direction is to the direction of the target axis of the radar, the higher the accuracy of the radar measurements. The problem of accurately detecting vibration in two directions (horizontal and vertical) in bridges has been solved using two independent radars [66,67].

2.1.3. Sonar

Sonar systems techniques are used to detect the scour profile in piers of bridges found in rivers or in quays of harbors and measure distances using various types of imaging devices. Multibeam and side-scan sonar for underwater detection have been used [68,69].

Hou S. et al. [70] developed a rapid underwater inspection method using a sonar device in which gathered data is analyzed by means of a deep convolutional neural network. The results show the feasibility of obtaining quantitative measurements for scour depth and damage.

2.1.4. Infrared Thermography

Infrared thermography is the technique of measuring infrared radiation emitted by bodies proportionally dependent on their superficial temperature. Infrared cameras are used to measure the emitted infrared radiation.

Infrared Thermography (IRT) has been developed to detect existing sub-surface deteriorations, including delamination and voids in concrete. When there is a delamination inside the concrete, the surface temperature is different from the sound area. With this feature, by scanning the surface of a concrete bridge, delamination can be detected [71].

Damaged areas can be detected as "hot spots" on the concrete surface temperature map. On the other hand, when the moist zones are required to identify, the "cold spots" are observed in intact concrete. It can be useful, especially for masonry or stone bridges.

In the case of application to delamination in concrete bridges, the IRT camera can also be installed on a vehicle with a normal moving speed to achieve faster inspection compared to other NDT methods [72]. Figure 2 shows an example of concrete scanning using a vehicle on which IRT cameras are stationed. The detection performance relies on temperature gradients, which means it is quite important to select the scanning time range in a day. Infrared thermography can be used to identify concrete elements in a structure under construction from a cloud of points due to the changes in temperature in the concrete along the hardening process. It may help to detect concrete elements in regions where the photo images are not clear enough due to deficient lighting. Poor or undesirable ambient light conditions produce low-quality images that significantly affect the accuracy of data extracted from related images and lead to a high level of errors. Thermal images offer more data than traditional digital photos. Temperature and humidity differences are the main parameters that are utilized to improve the quality of images for image processing. Pazhoohesh et al. [73] presented an innovative approach based on thermal image analysis to overcome problems related to image quality. Thirty preliminary tests and three case studies were implemented to show the feasibility of the method. A range of improvement between 8 and 48% was attained, which confirms the great potential of thermal images to overcome the limitations of image-based approaches. However, to a lesser extent, this technique has also been used to detect damages close to the surface of steel bridges [74,75].

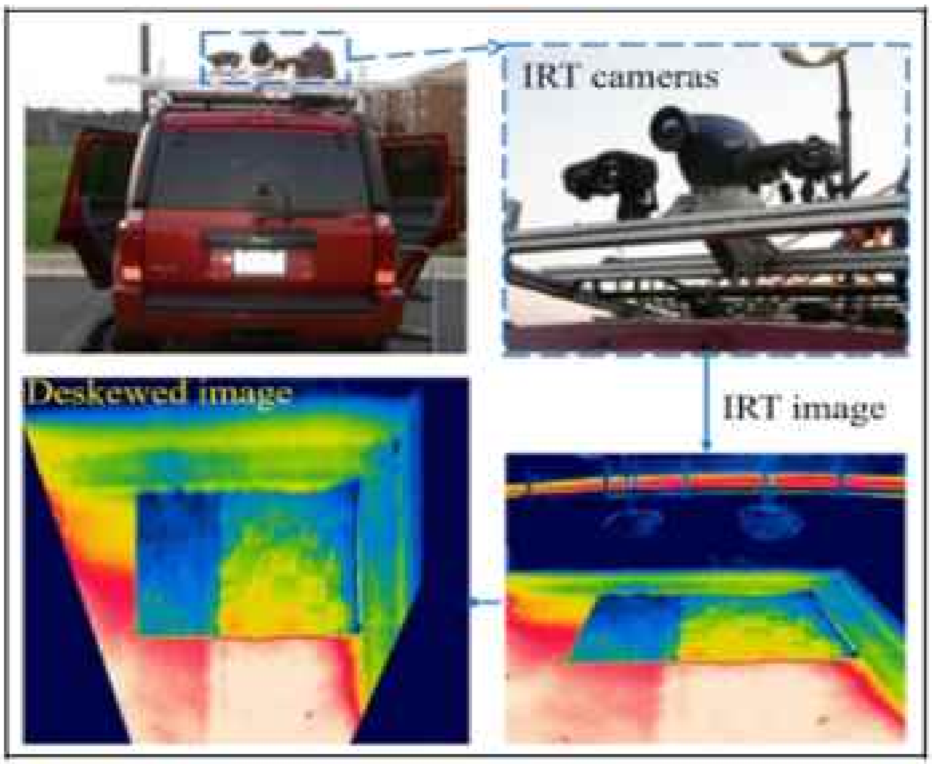


Figure 2. IRT camera setup on a vehicle and images from IRT camera (Reprinted with permission from Ref. [72], 2017, ASCE).

As shown in Figure 3, Matsumoto et al. [76] presented the time zone when the inspection can be executed. Watase et al. [77] investigated the favorable time windows for

IRT for concrete delamination evaluation by using plates with different thicknesses and delamination with different depths. The different thicknesses of the plate and the depth of delamination could influence the time window. Hiasa et al. [71,72] explored the time window for a good inspection of IRT by using experimental and numerical methods and found that optimal conditions for IRT implementation on concrete bridge decks were during nighttime under clear sky conditions. They also investigated the effect and correlation of delamination size and shape for using IRT through finite element modeling (FEM) and found that the delamination depth information could be estimated by incorporating IRT with FEM. In addition, discussed the considerations and issues in the application of IRT for concrete scanning at normal driving speeds, such as thermal contrast, time window, camera specification, distance, and utilization speed, and they gave detailed recommendations on how to address the mentioned issues. They also implemented a high-definition (HD) camera along with the IRT cameras to scan concrete to get visual images.

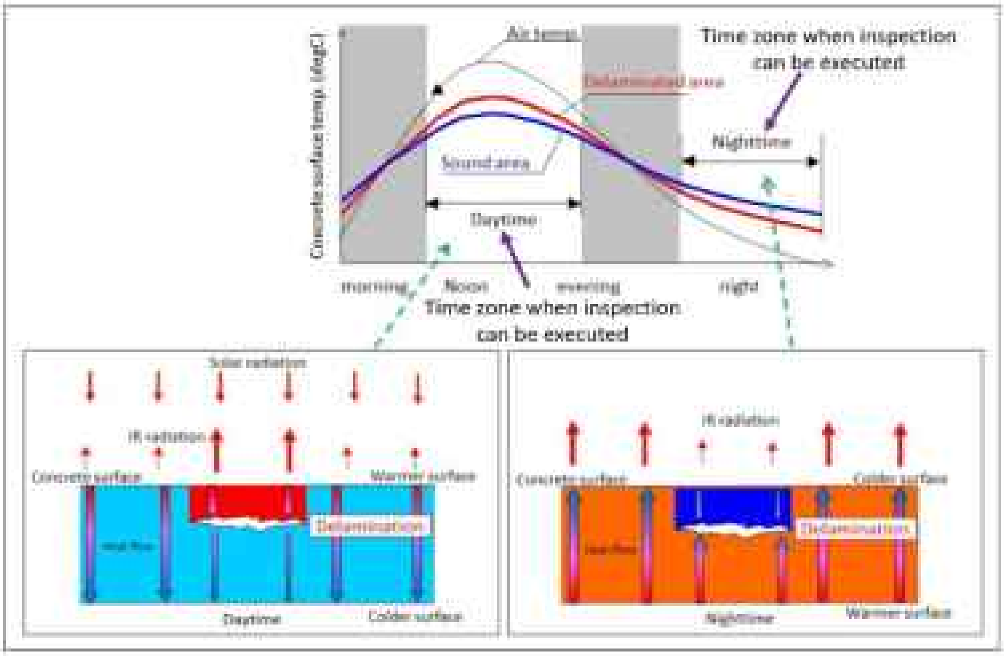


Figure 3. Diurnal temperature flow in a concrete structure with delamination.

The visual images from the HD camera could assist IRT in discarding false-positive predictions of delamination. The image processing approaches in the abovementioned applications are general image processing methods such as binarization, morphology, thresholding, gradient analysis, blob analysis, etc. Machine learning or deep learning methods can also be applied to process thermal images. Omar and Nehdi [78] used an unsupervised learning method, k-means clustering, to segment the mosaicked thermogram of the entire bridge deck and identify the objective threshold separately. Based on the different thresholds, the detection of delamination was performed with higher accuracy. In addition to using a vehicle to conduct concrete scanning, Ellenberg et al. [79] installed IRT cameras and an HD camera on UAV to scan pedestrian bridges. The color images collected from the HD camera were applied to identify the deck manually to support the location purposes of thermal images. By using the gradient-based threshold image processing method, the delamination areas were segmented from the thermal images. The UAV-borne thermal imaging system makes the IRT-based delamination detection become more flexible.

Additionally, this method allows for the assessment of thermal patterns within the bridge envelope. The accuracy of thermal measurements is influenced by both position accuracy and temperature accuracy. Proper calibration of thermal imagers is imperative for obtaining scientifically relevant data, ensuring accurate surface temperature measurements.

2.1.5. Photogrammetry

Photogrammetry has been defined by the "American Society for Photogrammetry and Remote Sensing" as the art, science, and technology of obtaining reliable information about physical objects and the environment through processes of recording, measuring, and interpreting photographic images and patterns of electromagnetic radiation and other phenomena.

Nowadays, photogrammetry has been adopted for many terrestrial applications in architecture, civil engineering, and industrial engineering. Since the emergence of digital cameras, this type of camera has been exclusively adopted for civil engineering applications. Camera calibration plays a crucial role in the photogrammetric process and significantly influences the final accuracy of the photogrammetric model.

Terrestrial photogrammetry was a relatively popular technique at the beginning of this century, with remarkable publications related to its application in bridge engineering. Particularly, the works of Jáuregui were some of the pioneer successful applications of photogrammetry to measure deformations during load tests [80–82] and later as a method for measuring vertical clearance during routine inspection of overpass bridges [83].

Terrestrial photogrammetry has also been considered for the creation of structural models of existing bridges, especially relevant to the case of masonry arch bridges where actual geometry is important and related to their structural stability. For example, photogrammetry was found to be very useful for the creation of an accurate 3D model of an arch ring of a bridge, modeling every one of its voussoirs that was lately integrated for both FEM and rigid block analyses [21]. A 3D model of the same bridge was lately used for different structural analyses considering their actual damage condition [84] or for further analysis considering different approaches: for example, elastic analyses taking into account the possible variations in the arch geometry [85]; or models that incorporate damage, elastoplasticity and contacts [86].

Overall, the accuracy and precision levels that this technique may offer, even when working with low-cost equipment, motivated its extensive use for infrastructure assets. Thus, Dai et al. [87] demonstrated that photogrammetric data can produce acceptable geometric models after comparing their models with other ground truth data collected by other highly accurate optical methods but at a very low cost.

Popescu et al. [88] assessed the performance of three imaging methods for 3D geometric modeling of existing concrete railway bridges: LiDAR, photogrammetry, and infrared scanning integrated into a 3D camera. They concluded that photogrammetry is the best equipment in terms of cost-efficiency.

2.1.6. Computer Vision: Image-Based Methods

Computer vision-based remote inspection and monitoring of bridges have been increasingly enabled through advances in displacement/strain measurement using optical flow or digital image correlation.

Computer vision can be applied at both local and global levels to monitor the condition and integrity of bridges [89] with the capability to detect surface defects such as concrete cracks/spalling and steel corrosion [90,91].

At the local level, computer vision techniques focus on analyzing specific components or areas of a structure. Cameras or imaging devices are employed to capture detailed images or videos of the targeted regions. Computer vision algorithms then process these data to extract valuable information. For example, cracks [92], crack propagation [93], corrosion [94], or other damage indicators can be detected and quantified using image processing techniques such as edge detection [95], pattern recognition [96], feature extraction, and image segmentation [97]. Local-level SHM provides detailed insights into the condition of specific areas, enabling targeted maintenance or repairs.

At the global level, computer vision techniques aim to monitor the entire structure or a significant portion of it. This involves deploying cameras or imaging devices strategically to capture images or videos of the structure from various angles and viewpoints. Computer vision algorithms analyze the collected data to identify global structural deformations, shifts, or movements. These algorithms can utilize techniques such as photogrammetry, optical flow analysis and processing images to track and quantify structural displacements or strains [98]. Global-level monitoring provides an overall view of the structural behavior and can assist in identifying potential risks, evaluating structural performance [99,100] and making decisions about structural modifications or interventions. Global-level applications also include human and vehicle load estimation applications [101,102] to not only monitor the structural responses but also to observe the external loads. Computer vision was used for bridge load testing to obtain load distribution, rating, and dynamic signature [103] as a portable and practical approach [104] with application with real-life multi-span bridges (Figure 4). This bridge, which carried the NASA Causeway over the Indian River, was constructed in 1964 and has a total length of 2993′ (912 m). Each span consists of 53 pre-stressed I-Beam spans, two flanking spans and a steel double-leaf bascule main span, which is 43 m, between trunnion centers. Each span of the Indian River Bridge is composed of 5 prestressed concrete girders approach spans having a composite reinforced concrete slab. AASHTO Type II Girders are used. A single span is shown in Figure 4.

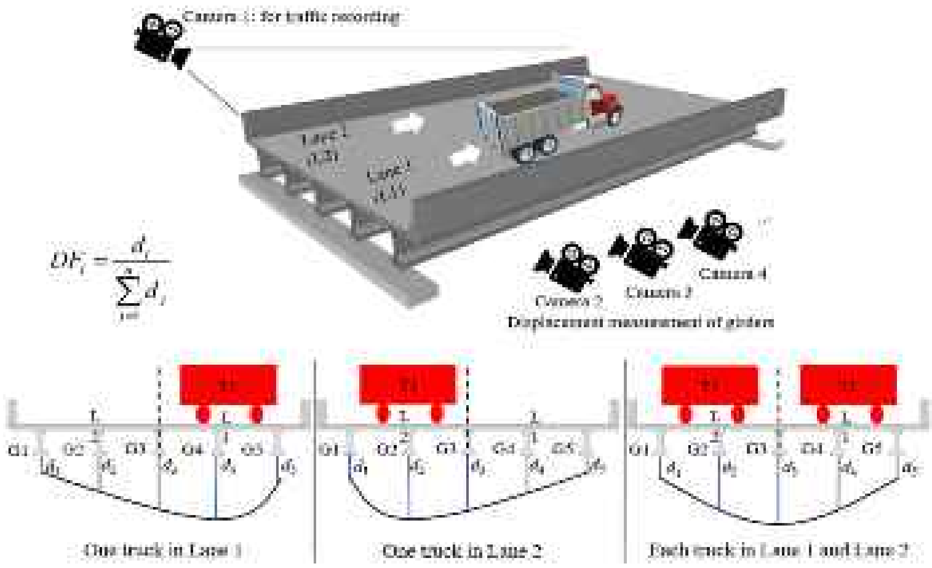


Figure 4. Distribution factor estimation in a bridge deck using computer vision systems (Reprinted with permission from Refs. [103,104], 2020, Springer).

Advances in remote sensing techniques, particularly in the areas of computer vision, have significantly enhanced the analysis and accuracy of bridge weigh-in-motion (WIM) systems. Micu et al. [105] obtained traffic flow and truck loads that were extracted from image data, and they identified the most critical load patterns for the Forth Road Bridge in Scotland. Zang et al. [106] presented a non-contact method using computer vision for weight identification and stability evaluation of exceptional vehicles. By integrating multispectral vision-based frameworks, as demonstrated by Gao et al. [107], non-contact WIM systems can achieve improved vehicle weight estimation and classification. Similarly, He et al. [108] showcase how computer vision techniques can refine the non-contact vehicle weighing process, utilizing bridge-based WIM frameworks for more accurate monitoring. Additionally, Yang et al. [109] demonstrate the effectiveness of hybrid systems that merge computer vision with in-pavement sensors to address challenges such as the wander effect in vehicle weight monitoring. These advancements underscore how remote sensing technologies, particularly computer vision, are driving the evolution of WIM systems, resulting in greater efficiency and precision in vehicle weight monitoring and traffic management.

By combining local and global-level monitoring using computer vision, engineers and stakeholders can gain comprehensive insights into the health and behavior of bridges.

AR/VR/MR Technologies for Remote Sensing

Extended Reality (XR) is an umbrella term that encompasses a range of immersive technologies, including Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR). XR has seen significant advancements and applications across various fields, such as entertainment, education, healthcare, industrial operations, and condition assessment of constructed engineering systems [110].

Effective data visualization techniques are crucial in improving the efficiency of condition assessment procedures in bridge health monitoring. While data analysis and evaluation play a significant role, visualizing the data in a clear and intuitive manner is essential for data interpretation and decision-making. Immersive visualization tools like VR, AR and MR offer distinct advantages in this context. These technologies provide interactive and immersive experiences, allowing users to engage with the data more intuitively. By utilizing immersive visualization methods, bridge health monitoring can benefit from enhanced perception, real-time data visualization, spatial context, collaborative decision-making, and training simulations.

In recent times, ensuring the safety and health condition of civil engineering structures has become critical. Therefore, the VR, AR, and MR tools have also been extensively used for structural condition assessment of bridges.

VR has been predominantly utilized for collaborative multi-user platforms, allowing multiple participants to engage in remote site visits and inspections without the need for physical presence. This capability significantly reduces the time and cost associated with travel and on-site inspections. For instance, engineers, inspectors, and other stakeholders can join a virtual environment from their offices, conduct thorough inspections, and make collaborative decisions based on real-time data and simulations [111].

AR and MR, on the other hand, have been instrumental in reducing the reliance on human labor and minimizing subjectivity in field operations. By providing digital virtual visual aids through head-mounted displays, these technologies assist inspectors and engineers in detecting and measuring defect sizes in structures. This augmentation not only improves the accuracy of inspections but also enhances the overall efficiency of the inspector's work by providing precise, contextually relevant information directly within their field of view [112].

XR is widely recognized as a valuable tool that can significantly enhance the efficiency and effectiveness of condition assessment procedures in the bridge domain. The immersive and interactive nature of XR technologies offers numerous benefits. These technologies enable engineers and professionals to visualize and interact with structural health data in a more intuitive and engaging manner. By providing realistic and spatially contextual visualizations, XR can aid in identifying and understanding potential issues or anomalies in bridges. This improved visualization leads to more accurate data interpretation, better decision-making, and more effective collaboration among stakeholders. As a result, XR is increasingly being adopted as a powerful tool to improve condition assessment procedures and ensure the safety and integrity of bridges.

2.1.7. Digital Image Correlation (DIC)

Digital Image Correlation (DIC) is a computer vision-based technique widely used for displacement and strain measurement comparing changes in images.

DIC has been implemented in many research works at the laboratory level. However, the application to full-scale bridges is still limited. The main applications have been in the measurement of deflections and monitoring of cracks in concrete bridges during load field tests [113–115]. Other applications have been in the measurement of the vibration of cables to derive the cable force [116,117] and displacements in masonry and steel bridges [118,119].

The accuracy of the displacements is similar to other traditional displacement sensors. Monitoring of cracks is affected by several variables, such as the weather conditions, the geometry of the bridge and the light conditions.

2.1.8. Robotic Total Station (RTS)

The total station technique combines an electronic distance-measuring device with an electronic theodolite.

The advent of a new generation RTS with a sampling rate of 10 Hz has offered the possibility of continuously monitoring structural dynamics. This type of RTS can be adapted to measure the vibrations of bridges. The RTS can directly measure the vertical and horizontal angles and distances between the RTS and the prisms with an automatic target recognition system that makes targeting easier and faster. The built-in program of the RTS can instantaneously and automatically compute the three-dimensional coordinates of the prisms from the measured angles and distances.

A typical total station can measure distances up to 2000 m with an accuracy of 2 mm. In the vertical direction, the accuracy is in the order of $\pm$0.1 mm [120]. In short-range measurements (D $\leq$ 100 m), all absolute errors are less than 1.0 mm. The background noise in RTS measurements for sighting distances varying from 25 m to 400 m only results in minor errors, which mainly distribute in a frequency range of less than 0.1 Hz. Fortunately, the frequency range of the RTS noise does not overlap with that of the bridge vibrations, which are mainly distributed between 0.1 and 10 Hz [121].

2.1.9. Global Navigation Satellite Systems (GNSS)

GNSS can provide dense time series of absolute positions in a reference frame with great stability over long periods and without requiring integration of observations like accelerometers.

Global Positioning System (GPS) was the first satellite positioning system developed by the US Navy in the 1970s. It became operational in 1993, with 24 satellites orbiting the Earth, and was fully available for public use in 2000. GPS is now regarded as a mature technology, alongside extensometers, inclinometers and lasers of various forms. GPS appears to be a standard choice for long-span bridges, but below a certain span length, it is degraded compared to optics-based systems with 3D capability, of which the present best solution is the total station. GPS gives a global three-dimensional position at precise times and at rates of up to 100 Hz. Obtaining deformation was the primary aim, but because of the precise time measurement element, frequencies of vibration are also measured implicitly.

GPS, unlike other sensors, is readily able to provide three-dimensional absolute position information at a rate of 20 Hz and higher rates if necessary. This enables the analysis of the frequency response and, by using multiple receivers in strategic locations, the dynamics of the vertical profile.

GNSS stations are already present in bridge monitoring applications, mainly for the determination of reference points for other sensors or to transfer optical or topometric data to a specific reference frame, but rarely as an acquisition tool itself. Over the last decade, with the ever-increasing performance of GNSS hardware, several studies assessed the performance of GNSS for dynamic monitoring [122], and their application in the monitoring of long-span bridges has been a subject of increasing interest and research. For example, Kaloop and Li [123] used GNSS receivers to characterize changes in the behavior of a cable-stayed bridge due to the apparition of cracks. Yi et al. [124] and Wang et al. [125] showed that high-rate GNSS receiver can be used to monitor long-span bridges response to both environmental and traffic loads. Ogundipe et al. [126] used a small network of GNSS stations to monitor a steel box girder viaduct bridge in the UK and successfully detected the three main frequencies of the structure. GNSS and Earth observation (EO) technologies have been used in the remote monitoring of the Forth Road Bridge (Scotland, UK), which is a 2.5 km long suspension bridge across the Firth of Forth connecting Edinburgh and the Northern part of Scotland [127].

A relevant problem in the use of GNSS is its high cost. To solve this issue, Manzini et al. [122] have investigated the performance of an identified optimal low-cost GNSS station in dynamic scenarios. They demonstrated that with proper processing parameters and a short baseline, the proposed GNSS solution with 1 Hz sampling proved able to detect and qualify subcentimetric quick displacements and 1 cm oscillations with frequencies up to 0.25 Hz. Such results confirm that low-cost hardware can provide data with enough accuracy to monitor typical phenomena of slender structures, such as long-span bridges. Both longitudinal and vertical responses of the main span to the thermal load of the Aquitane Bridge in France were successfully observed with GNSS data on various points of the structure.

GNSS and GPS have permitted the observation of dynamic deflections in bridges, initially of long flexible ones (with main vibration frequencies lower than 1 Hz), and more recently of short to medium-span bridges, stiffer and with modal frequencies higher than 1 Hz, and with a small signal-to-noise ratio (SNR), in some cases lower than 1. However, some drawbacks have been identified in some real applications. In this sense, the paper by Stiros [128]: (i) discusses structural constraints, experimental evidence, and serviceability limits of bridges as constraints to GNSS monitoring; (ii) examines a representative case of careful monitoring of a reinforced concrete road bridge with reported excessive dynamic deflections; and (iii) explains such deflections as a result of a double process generated by large reflective surfaces of passing vehicles near the antenna; first corruption/distortion of the satellite signal because of high-frequency dynamic multipath, and second, shadowing of some satellites; this last effect leads to a modified observations system and to instantaneously changed coordinates and deflections. Transient shadowing of some satellites by vehicles and the associated dynamic multipath are effects critical for monitoring bridges, and they may highly influence the quality of results in low SNR conditions. Distortion of the GNSS signal under these conditions is not easily recognized because it correlates with passing vehicles, and it may be assumed that it reflects a structural response to dynamic loading. Such effects are critical in short bridges but minimized at the mid-span of long-span bridges, with large deflections deriving on SNR higher than 1 and lower interference from the passing vehicles. Therefore, the interpretation of the results from GNSS for short and medium-span bridges should be done carefully and, in some cases, by comparison with other monitoring techniques. Otherwise, the high vibration amplitudes obtained from the post-processing can be wrongly interpreted as due to structural damage while the bridge is in good condition.

Under normal conditions, the sampling rate of GPS/GNSS is nowadays up to 100 Hz, while the accuracy of isolated measurements of displacements/oscillations with frequencies up to 4 Hz is better than 20 mm for simple differential and for Precise Point Positioning (PPP) post-processing techniques. Therefore, this technique is very well-suited for long-span bridges with frequencies typically below 1 Hz and vibrations with amplitudes in the range of 10 to 100 cm.

For bridge inspection, Artese and Zinno [129] used a terrestrial laser scanner to scan a single straight line under a bridge to obtain dynamic deformation when a dynamic load is applied during a load test, as shown in Figure 5. The TLS was equipped with a GNSS system to be synchronized with the moving load, which is also monitored using a digital camera with integrated UTC time. The line of points obtained at different timestamps were interpolated using cubic polynomials. The method was tested in three different bridges and verified to provide reliable measurements to estimate the behavior of structures.

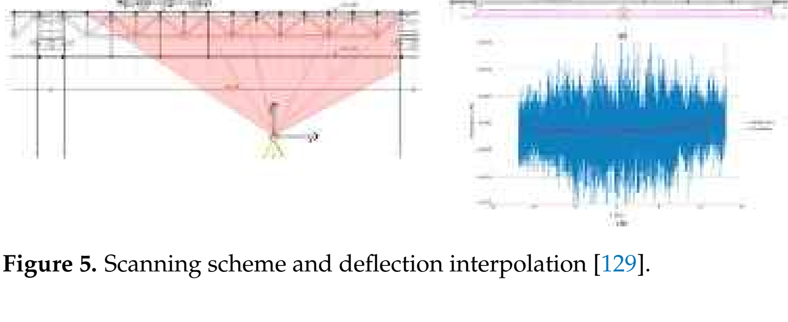


Figure 5. Scanning scheme and deflection interpolation [129].

A summary of the described techniques and their feasible applications to bridges, as well as advantages and limitations, is presented in Table 1.

Table 1. Summary of most used remote sensing technologies in bridge engineering.

Technology	Key Aspects	Applications	Advantages	Limitations
Laser Scanning	Offers both static and mobile modes for detailed geometric modeling and monitoring of deformations.	Bridge inspection, deformation monitoring, geometric modeling, load test measurements.	High accuracy in capturing 3D geometry is useful for large-scale inspections.	Requires post-processing for interpretation limited in dynamic situations.
Radar	commonly used for remote displacement measurements. Ground-based and satellite-based	Monitoring displacements, bridge deflections, slope stability, subsidence, and scouring.	Effective for long-range and long-term displacement measurements.	Data interpretation can be complex, and radar signals may be affected by environmental factors.
Infrared Thermography	Detects temperature differences on surfaces to identify subsurface defects, such as delaminations or moisture.	Inspection of concrete, masonry, and steel bridges to detect cracks, delaminations, or moisture damage.	Detects subsurface defects and damage without direct contact.	Less effective for serious damages. Sensitive to temperature gradients and environmental conditions
Photogrammetry	Cost-effective for creating detailed geometric models, especially for arch bridges.	Masonry and arch bridges.	Cost-effective and efficient for creating 3D structural models.	Accuracy depends on camera calibration. External factors like lighting can affect results.
Computer Vision	Using image processing techniques to detect surface defects or global deformations	Local and global monitoring of structural integrity, including cracks and corrosion.	Provides detailed information on surface defects and global deformations.	Requires significant data processing and algorithm development for accurate results.
Digital Image Correlation (DIC)	precise strain and displacement measurements by comparing images over time.	Bridge deformation monitoring, crack detection, load test analysis, and cable force monitoring.	High precision in displacement and strain measurements.	Limited to surface deformations. Weather and lighting conditions can affect image quality.
Robotic Total Station (RTS)	Track structural displacements with high accuracy. Suitable for monitoring dynamic behavior in bridges.	Tracking structural vibrations and dynamic behavior and monitoring of bridge components with high precision.	Accurate dynamic displacement measurement and vibration analysis.	Line of sight to prisms needed to be limited to short-range measurements.
Global Navigation Satellite Systems (GNSS)	Provides 3D coordinates for dynamic monitoring, offering continuous displacement data over time.	Well suited for monitoring long-span bridge deflections and dynamic displacements.	Continuous monitoring with real-time data.	Expensive hardware is affected by signal interference in short-span bridges or obstructed environments.

2.2. Platforms

2.2.1. Ground-Based Systems

This is the original way how remote sensing was carried out at the beginning, being the easiest way to obtain data from a camera, video or Lidar system. However, in the case of large structures, such as bridges, the fixed position of the sensors can result in important measurement errors and missing information on relevant parts of the bridge.

2.2.2. Terrestrial Mobile Systems

Terrestrial robots are used in the inspection and non-destructive testing of bridges. The robots are equipped with various sensors, cameras, and other measurement devices (ground-penetrating radar (GPR), impact echo (IE), ultrasonic surface wave (USW), Light Detection and Ranging (LiDAR) sensor, Inertial Measurement Unit (IMU), and GPS receiver) to collect data on the bridge's condition [130–133].

2.2.3. Airborne Platforms

This chapter provides a state-of-the-art review of the application of Unmanned Aerial Vehicles (UAVs) for the remote SHM of bridges. The use of UAVs in this context has gained prominence due to their ability to access hard-to-reach locations, gather detailed information, and enhance the efficiency and safety of bridge inspections. The chapter covers various aspects, including types of drones, sensors used, types of measurements, accuracy considerations, limitations, path planning, and vibration-based measurements.

Drones as an Innovative Platform for Bridge SHM

Unmanned Aerial Vehicles (UAVs), commonly referred to as drones, are aircraft devoid of onboard pilots. They have emerged as a revolutionary tool for enhancing the quality of inspections by providing information and details that may be impractical or costly to obtain using traditional access methods [134].

The significance of UAVs in the field of bridge SHM lies in their capability to access challenging locations and gather detailed information. Traditional inspection methods often rely on human-based visual assessments using scaffolding, ropes, elevating platforms, or specialized vehicles (e.g., by-bridge). However, these methods are not only time-consuming and expensive but also pose safety risks to inspectors. We recall that the construction industry is statistically one of the most dangerous workplaces globally. Moreover, the interruptions caused by traditional inspections are also mitigated through the swift and non-disruptive nature of UAV operations.

Types of Drones

UAVs utilized for bridge SHM are predominantly characterized by their vertical take-off and landing capabilities. This category includes tricopters, quadcopters, hexacopters, and octocopters, depending on the number of motors [135]. Figure 6 illustrates the main components of a quadcopter, showcasing its integration with essential devices and sensors for measuring SHM-related quantities.

The applications of drones in remote sensing of bridges span various purposes globally. Equipped with cameras, sensors, and intelligent devices, drones are used in daily imaging, package delivery, mapping, and visual inspections of challenging locations.

In typical civil infrastructure monitoring applications, a recommended bridge inspection procedure using drones typically involves four key stages [134]:

- A bridge information review to determine critical information regarding the bridge structure;
- A site risk assessment to determine potential risk zones for the operation of the drone;
- A drone pre-flight setup to ensure flight safety by checking the condition of hardware components, updating the software, and flight path planning;
- A drone-enabled bridge inspection to obtain a close-up view of the areas of interest based on a preplanned path flight;
- Damage identification: The structural components are recreated in a 3D virtual space using photogrammetric software to observe the bridge and its possible damages from different angles.

Figure 6. A presentative UAV equipped with different components for vibration measurement (Reprinted with permission from Ref. [136], 2023, Elsevier).

Sensors for Drone-Based SHM

Drones employed for SHM integrate a variety of sensors to assess the condition of infrastructure and detect potential issues [137]. Common sensors include [138]:

- RGB cameras to capture high-resolution images for visual inspection, identifying surface cracks, corrosion, or visible damage;
- LiDAR sensors create detailed 3D maps of structures, allow for precise measurements, and identify deformations or structural shifts.
- Thermal cameras: infrared sensors detect variations in surface temperatures and identify anomalies indicative of hidden structural problems, such as insulation issues or water ingress.
- GPS and GNSS receivers provide accurate location data for the creation of geospatial models and tracking structural changes over time.
- Environmental sensors measure humidity, temperature, and other environmental factors to provide data on the conditions affecting structural health and potential degradation.

Types of Measurements

UAVs are mostly used for geometrical measurements of structural components and the reconstruction of 3D structural models. Congress et al. [139] present a methodology and its feasibility for conducting 360° inspections of various bridges using 3D models and orthomosaics generated from aerial images collected using UAVs. The Minnesota Department of Transportation conducted a study to verify the feasibility of using a combination of optical and infrared images and videos for bridge inspection and to generate 3D models of the area [140]. The Oregon Department of Transportation identified major bridge-reporting categories and provided a scale to rate the usefulness of UAVs for bridge inspections [141].

Additionally, specialized software allows for the measurement of distances, dimensions of structural elements, and the monitoring of span deflections over time in bridges caused by increasing loads or long-term effects [79]. The accuracy of geometrical measurements is affected by factors like camera resolution, sensor size, uncertainty in image positions, and calibration methods [142].

The growing emphasis on extracting quantitative information from images plays a pivotal role in the structural health monitoring of bridges through drones. This involves the identification of deterioration regions and crack detection. Studies, such as Ellenberg's investigation into the effectiveness of drones in detecting cracks concerning distance to the structure [143], demonstrated that high-resolution cameras can detect crack thicknesses as small as 0.75 mm at a distance of 3 m. Other studies, as reported in [144], have visually identified cracks as small as 0.3 mm at a distance of 10 m, emphasizing the importance of image quality parameters such as sharpness, exposure, and minimal noise.

Advancements in robotics and machine vision are opening up exciting possibilities for vibration measurement. Hoskere et al. [145] conducted an experiment where they derived the natural frequencies and corresponding mode shapes of a 10 m pedestrian suspension bridge by analyzing videos captured with a UAV-mounted camera. Notably, the UAV was manually controlled as opposed to utilizing path planning. For automatic target detection, fiducial markers were employed on the structure, and the KLT algorithm was employed to track these markers on the bridge. The error in natural frequencies was found to be 1.6% when compared to accelerometer data. The frequencies extracted fell within the range of 0.5 Hz to 2 Hz, as a high-pass filter with a cutoff frequency of 0.5 Hz was applied to eliminate hovering motion, effectively removing low-frequency components from the bridge vibration data. Tian et al. [116] utilized vibration data obtained from a camera mounted on a UAV to measure cable forces in a highway suspension bridge with dimensions of 2040 m in length and 49.7 m in width.

Infrared thermography, when supported by drones, emerges as a powerful, non-destructive method for evaluating bridges without direct contact. The utility of infrared thermography extends to identifying the types of materials used (e.g., masonry and concrete), detecting the presence of steel rebars, and identifying water leakages or humidity issues [146].

Path Planning

Path planning is a critical aspect of deploying UAVs for SHM. It involves determining optimal routes for UAVs during inspection missions, impacting efficiency, power consumption, and overall safety. Effective path planning is essential for avoiding collisions, adapting to environmental changes, and ensuring robust performance in adverse conditions such as high winds [147].

In the context of bridge health monitoring, path planning is crucial for optimizing the efficiency of inspections. It minimizes power consumption, enhances safety by avoiding obstacles, and ensures reliable data collection. This is especially important when dealing with complex structures such as bridges, where precise route planning contributes to the overall success of the mission.

Geometrical Measurements and 3D Model Reconstruction

The section presents detailed case studies of bridge inspections using drones for 3D model reconstruction.

The Río Claro Bridge, situated in Colombia, is a case study where researchers (Perez Jimeno et al. [148]) employed a methodology involving both pre-planned and free-flight missions to capture a wide dataset of aerial imagery. The subsequent processing of these images resulted in the generation of a detailed 3D model of the bridge (Figure 7), enabling a thorough assessment of its structural integrity. The drone-based inspection revealed a multitude of defects that had eluded detection during traditional visual inspection methods, emphasizing the potential capabilities of this technology.

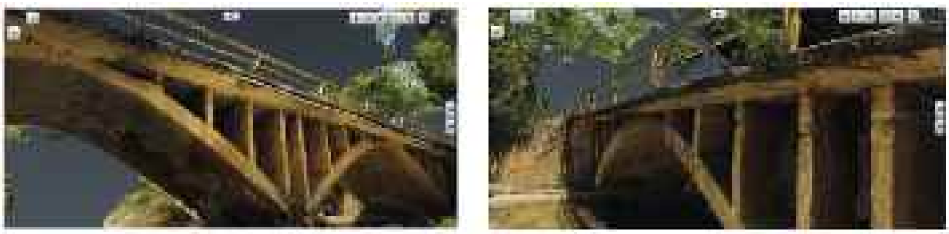


Figure 7. 3D model of the case study bridge: upstream view and downstream view [148].

Congress et al. [139] studied three distinct bridges located in Alaska: Montana Creek Bridge, Canyon Creek Pedestrian Bridge, and Eagle River Southbound Bridge. Each bridge underwent a 360° inspection using drones, demonstrating the adaptability of this approach to diverse bridge structures and environments.

Montana Creek Bridge: This steel-truss bridge with a timber deck presented a challenge due to its limited vertical clearance over the creek. To address this challenge, a small drone was utilized for under-bridge inspections, revealing corroded areas, bent truss elements, rubble accumulation, and timber tie conditions. The 3D model and orthomosaics generated from the drone data proved a valuable resource for further analysis and damage assessment.

Canyon Creek Pedestrian Bridge: Despite its dense surrounding vegetation, the Canyon Creek Pedestrian Bridge was effectively inspected using a drone. The high-resolution 3D model and orthomosaics revealed spalled curbs, rusting, paint peeling, efflorescence staining, and potential support erosion. The ability of drones to capture imagery from various angles, including under-bridge views, enabled the detection of defects that might have been obscured by vegetation during traditional visual inspections.

Eagle River Southbound Bridge: This bridge, with its fast-flowing stream beneath, posed a safety challenge for traditional inspection methods. Drone technology overcame this challenge by allowing for strategic positioning of multiple drones on opposite abutments. The generated 3D model and orthomosaics identified patched areas, cracks, and efflorescence. The use of drones reduced the need for inspectors to work in hazardous environments to enhance their safety.

The case studies provide evidence that drone-based bridge inspections represent a transformative approach to structural health monitoring. The ability of drones to capture extensive imagery, generate detailed 3D models, and operate in challenging environments makes them a valuable tool for bridge inspectors.

Deterioration Regions and Crack Detection

This section delves into the analysis of deteriorated areas and cracks in bridges using drone monitoring, with a focus on automated software employing artificial intelligence (AI) algorithms for damage estimation. Traditional crack detection methods relying on human visual inspection have limitations in terms of expertise, time, and accessibility. Using drones equipped with innovative sensors and processing the acquired images with AI algorithms makes it possible to overcome these limitations, as demonstrated in the following case study examples.

Potenza et al. [149] discussed the implementation of a software named DEEP (DEfect detection by Enhanced image Processing) for evaluating defects in bridge structures through image processing. The study demonstrates DEEP's effectiveness in detecting structural objects and defects, showcasing its potential to improve inspection processes.

Kim et al. [150] focused on crack identification on a concrete bridge using image processing from a commercial UAV equipped with a high-resolution camera. The algorithm calculates the crack length and thickness thanks to the comparison to markers installed on the bridge. Figures 8 and 9 show the procedure of crack length and thickness estimation.

The application of deep learning algorithms based on Convolutional Neural Networks (CNN) is also highlighted in the case study of the D Bridge in Gangwon province, Korea, as described in [151]. The researchers performed a comparison between traditional visual inspection and UAV-based inspection, which suggested that the latter proved to be more accurate, identifying efflorescence and some cracks that have been overlooked by the human eye.

Vibration-Based Measurements [152,153]

This section discusses the use of UAVs for vibration-based measurements through various sensors equipped on the drones.

Figure 8. Experimental setup [150].

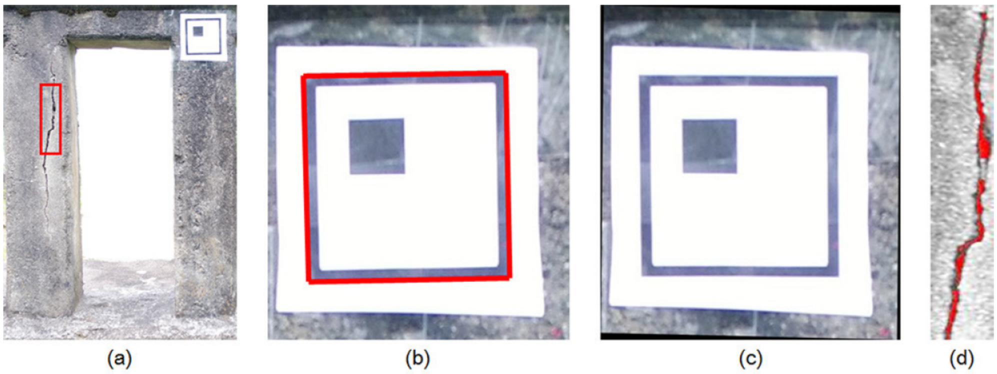


Figure 9. Image processing procedure for crack length and thickness estimation: (**a**) image acquired by the drone, (**b**) marker detection, (**c**) estimation of the pixel size, and (**d**) crack characteristic estimation [150].

Carroll et al. [154] introduce an innovative approach to monitoring the structural condition of civil infrastructure using vibration-based measurements. This method involves deploying customized sensor packages distributed via drones to collect acceleration data from structures. The collected data were then analyzed using a technique called B-Spline Impulse Response Function (BIRF) to extract the Dynamic Signature Response (DSR), which can indicate structural damage or changes over time. Key components of the system include the sensor package, the drone, and the damage identification method. The sensor package consists of electronics for data gathering, storage, and wireless control, along with a docking mechanism utilizing an electropermanent magnet and a power supply (battery). This package is designed to be lightweight, self-powered, and capable of collecting acceleration data from structures. The drone platform is based on a hexacopter and is used for secure deployment and retrieval of sensor packages in hard-to-reach locations. The damage identification method utilizes the BIRF technique to extract the DSR from experimental vibration measurements. The study validates the developed system through laboratory experimental tests, demonstrating successful drone-based deployment, accurate data collection, and damage detection. Figure 10 shows the steps of the test.

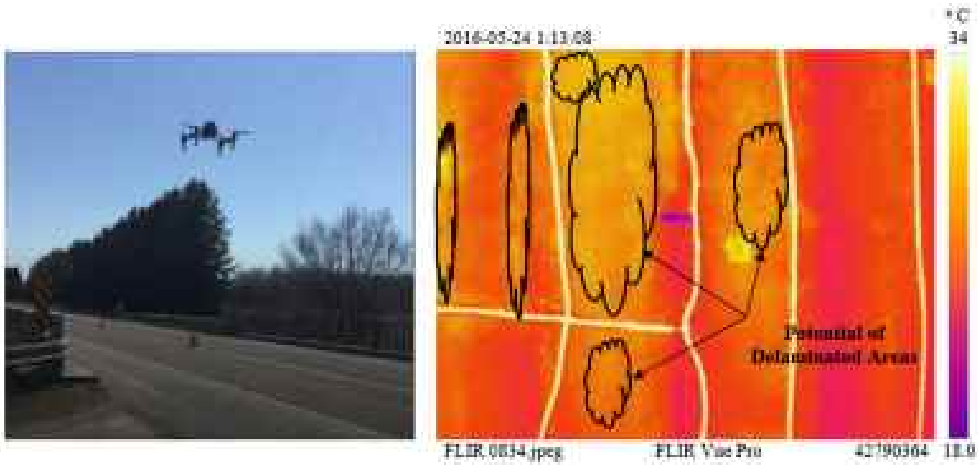
Figure 10. Photos of the sensor deployment and retrieval experiment [154].

Marchisotti and Zappa [155] discussed another approach to vibration-based measurements using drones for modal analysis. This method involves a vision-based measurement system consisting of a grayscale camera, a time-of-flight (ToF) sensor, and a tracking camera mounted on a drone. The system allows for the measurement of resonance frequencies and the reconstruction of modal shapes of structures. The system compensates for drone movement effects on vibration measurements and reconstructs the structure's 3D geometry for modal analysis. Laboratory experiments and outdoor tests demonstrated the effectiveness of the proposed technique in accurately measuring resonance frequencies, reconstructing modal shapes, and identifying structural changes or damage.

Infrared Thermography

Concrete emits infrared radiation influenced by temperature and emissivity. Thanks to infrared sensors equipped with drones, it is possible to perform a scan of the structure and detect any damaged surfaces or thermal bridges.

The study in [78] detected subsurface delamination in concrete bridges using UAV thermal imaging and validated the results with non-destructive testing. Two reinforced concrete bridges were surveyed using a UAV-borne thermal imaging system. The system employed a FLIR Vue Pro infrared thermal camera. Pre-flight preparation involved configuring camera settings and considering environmental factors like temperature and sun direction. Thermal camera data were visualized to identify delaminated areas based on temperature differences. Digital images were taken alongside infrared data for comparison analysis. Thermal data were utilized to generate contour plots indicating different severity levels of delamination. The results were represented on condition state maps like the one in Figure 11.



(**a**) (**b**)

Figure 11. (**a**) UAV during the thermal inspection and (**b**) thermal image indicating potential delaminated areas. (Reprinted with permission from Ref. [78], 2017, Elsevier).

Thermography was also employed by [55] evaluating the 360-degree inspection of bridges using UAVs. It identified structural problems such as cracks, spalling, efflorescence, and rust.

2.2.4. Satellite

In general, the level of detail that a satellite can see depends on several factors, including the altitude of the satellite, the size of its sensor, and the type of sensor technology it uses. For example, low Earth orbit (LEO) satellites, which are typically located between 160 and 2000 km (100 and 1200 miles) above the Earth's surface, can capture images with a higher level of detail than geostationary satellites, which orbit at an altitude of about 36,000 km (22,000 miles) and cover a larger area but with lower resolution. Geostationary satellites are a type of artificial satellite that orbits the Earth at an altitude of approximately 36,000 km (22,000 miles) above the equator. These satellites move at the same rate as the Earth's rotation, which allows them to remain in a fixed position relative to a specific point on the ground, making them ideal for telecommunications, weather monitoring, and other applications that require constant communication with a specific location on Earth. Modern satellites can capture images at sub-meter resolutions, which means that each pixel in the image corresponds to less than one meter on the ground. This level of detail is sufficient for many applications, such as mapping, monitoring crop health, and tracking urban growth. However, as mentioned, newer satellites are capable of capturing even higher-resolution images with pixel sizes as small as 10 cm (4 inches). This level of detail enables applications such as monitoring infrastructure, identifying changes in urban areas, and detecting small objects on the ground. It is important to note that the level of detail that a satellite can capture is also affected by environmental factors such as cloud cover, atmospheric conditions, and the angle of the sun. Additionally, the quality of the imagery also depends on how the data are processed and analyzed after being captured by the satellite. Alani et al. [156] used these methods in the analysis of specific points and monitoring of time series and their deformation. In particular, the horizontal displacement of the old bridge in Aylesford (UK) was measured for a period of several years. This can be a valuable monitoring tool for the scouring of bridge piers, as presented in [157].

2.3. Advanced Data Processing Using Machine Learning Techniques

Deep Generative Models (DGMs) have gained significant popularity in recent years across various disciplines [158]. These models leverage the power of deep neural networks (hence "Deep" Generative Models) to learn hidden data representations and generate new data instances with variations. DGMs offer a flexible and effective approach to modeling complex data distributions [159].

Through the training process, DGMs learn the underlying patterns and dependencies in the data [160]. This enables them to generate new data points that are similar to the data points from the unknown distribution. By capturing the complex relationships and variations present in the training data, DGMs can generate new instances that exhibit similar characteristics and follow the learned data distribution.

DGMs encompass various architectures and methods for learning and generating data (Figure 12). Six common members of DGMs include Autoregressive Models (AMs), Variational Autoencoders (VAEs), Flow-based models (FBMs), Energy-based Models (EBMs), Generative Adversarial Networks (GANs), and Diffusion Models (DMs). Autoregressive models generate data sequentially by modeling the conditional probabilities [158–160]. VAEs learn compressed representations of data and generate new samples from the latent space. FBMs apply invertible transformations to a simple base distribution to model the data distribution directly. EBMs assign energy scores to samples to determine their probability. GANs involve a generator and discriminator network to generate realistic samples. DMs model the process of data diffusion over time. Each member offers unique capabilities and is chosen based on the specific characteristics of the data distribution being modeled.

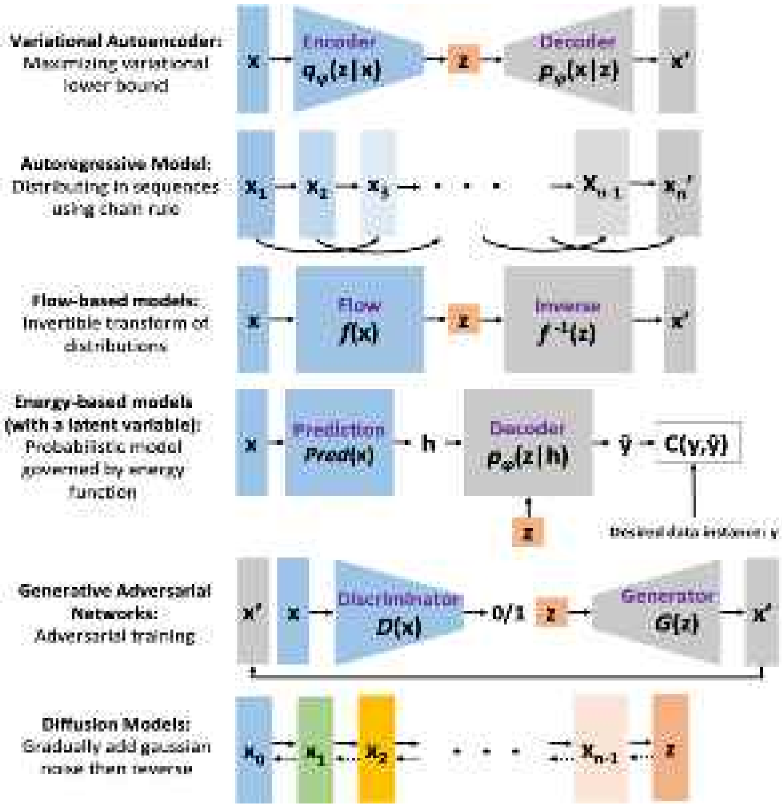


Figure 12. Overview of the Deep Generative Models (Reprinted with permission from Ref. [111], 2023, Springer).

DGMs can offer valuable solutions for addressing the data scarcity issue in SHM. For instance, in situations where there is a limited amount of labeled or high-quality data, DGMs can provide distinct ways to generate data, overcoming the challenges posed by data scarcity [161]. These approaches are as follows:

(1) Data Generation: DGMs can generate new data instances, which can be useful for general data needs or increasing the overall dataset size. (2) Lost Data Reconstruction: DGMs can reconstruct lost or missing data points, filling in the gaps in the dataset. (3) Data Augmentation: DGMs can be used to augment the existing dataset, addressing class imbalance issues in classification problems by generating synthetic samples for underrepresented classes. (4) Data Domain Translation: DGMs can translate data between different domains, such as transforming undamaged data to damaged data, even when direct access to paired data is limited. (5) Data Denoising and Repairing: DGMs can clean and repair noisy or low-quality data, enhancing the quality and reliability of the dataset. (6) Anomaly and Novelty Detection: DGMs can detect anomalies and novelties in the data, allowing for the identification of unusual or previously unseen patterns. (7) Other Applications: DGMs can also be utilized for tasks such as damage identification, reducing annotation requirements through transfer learning, and exploring new approaches yet to be fully explored in SHM.

The use of VAEs in SHM can be traced back to the early 2020s, with studies focusing on anomaly detection in railways and feature extraction using VAEs [162]. Since then, several research studies have leveraged the generative capabilities of VAEs in civil SHM for various purposes. Some of these include damage and anomaly identification, condition assessment, and optimal sensor placement, all aimed at addressing the data scarcity challenge in the SHM domain of bridges. The use of VAEs in SHM has shown promise in capturing and modeling the underlying data distribution, enabling effective anomaly detection and feature extraction. These studies highlight the diverse applications of VAEs in SHM and their ability to address data scarcity issues. By utilizing VAEs, researchers and practitioners can enhance the capabilities of SHM systems for identifying damage, assessing conditions, optimizing sensor placement, and dealing with limited data availability, ultimately improving the overall efficiency and effectiveness of SHM practices.

In the field of bridge health monitoring, AMs have gained popularity among researchers over the years. They have been primarily utilized for feature extraction in damage identification using Autoregressive Moving Average (ARMA) or its variants [163]. The use of GANs, including the original GAN and its variants, has gained significant attention in bridge SHM applications [164]. By employing these various approaches, DGMs can enhance the performance, robustness, and generalization capabilities of data-driven tools used in SHM applications, particularly in situations where data availability is limited. These methods enable researchers and practitioners to overcome the challenges associated with data scarcity, leading to more reliable and effective analysis and decision-making in SHM.

2.4. From Scan to BIM (From Point Cloud to IFC)

Scan to BIM is the process of converting scanned data, typically point clouds, into Building Information Modeling (BIM) models. This process involves several steps, including point cloud data cleansing, data registration, data segmentation, and object recognition. Point cloud data cleansing is the process of removing noise and outliers from the point cloud data. This is necessary because the accuracy and quality of the resulting BIM model are directly dependent on the quality of the input data. Point cloud data cleansing can be done manually, but it is often automated using software tools that can identify and remove noise and outliers. Data registration is the process of aligning multiple point cloud scans together to create a single, cohesive point cloud. This is important because it allows for a more complete and accurate representation of the scanned area. Data registration can be done manually, but it is often automated using software tools that use common features between scans to align them.

Data segmentation is the process of dividing the point cloud into smaller regions or segments. This is important because it allows for the analysis of specific regions or objects within the point cloud. Data segmentation can be done manually, but it is often automated using software tools that can identify and group similar points together.

Object recognition is the process of identifying and classifying objects within the point cloud. This is important because it allows for the creation of more accurate and detailed BIM models. Object recognition can be done manually, but it is often automated using machine learning algorithms that are trained on labeled data sets.

Once the point cloud data have been cleaned, registered, and segmented, and objects have been recognized, the next step is to create a BIM model. This involves creating a 3D model using the point cloud data as a reference. The BIM model can be exported as an Industry Foundation Classes (IFC) file, which is a common format used in the construction industry for sharing BIM models.

The main difficulties in the field of scanning applied on bridge point clouds are encountered in obtaining semantically meaningful bridge information models in an automated way. As an example, Hajdin et al. [165] presented a novel modular framework with procedures for the automated provision of BIM models from 3D point clouds for existing road bridges. The method is based on artificial neural networks (ANN). In the following case studies, some practical examples of the transition from Scan to BIM and FEM are presented.

3. Case Studies

The following examples show several case studies of using remote sensing in bridges based on the author's own experience.

3.1. Tajo River Arch Bridge in the High-Speed Railways Network of Spain (Ground-Based Radar)

This case study shows the possibilities of the radar technique in the monitoring of large bridges.

3.1.1. Identification and Description of the Case Study

The purpose of routine load tests is to ensure that bridges meet design and construction standards. These tests involve applying controlled loads both statically and dynamically to the bridge and then measuring displacements, strains, and accelerations. However, measuring displacements relative to a fixed position can be a difficult task, as was the case with the routine load tests conducted on the El Tajo and Almonte viaducts in Extremadura, Spain [166]. These viaducts span different branches of the Alcántara-Garrovillas reservoir and are part of the Madrid-Extremadura High-Speed Line, which runs through the municipalities of Garrovillas de Alconetar and Santiago del Campo in Cáceres. The viaducts consist of two approaches and one central section, with the El Tajo Viaduct having approaches and central spans ranging from 45 to 60 m, and the Almonte Viaduct having approaches and central spans ranging from 35 to 45 m. The longest span is constructed with concrete arches of varying width and thickness, with El Tajo having a main span of 324 m and Almonte having a span of 384 m in length. The columns on the arches reach their apex at a height of 70 m above the river [167–169].

3.1.2. Selection and Description of the Best Remote Sensing Technique

Due to the dimensions of the bridges and the problem of measuring displacements with standard instrumentation as LVDT, in both El Tajo and Almonte Viaducts, an IBIS-FS was utilized (as shown in Figure 13), and data analysis was conducted using a MATLAB toolbox. For both cases, 9 and 11 reflective targets were installed, respectively. The GB-InSAR was installed at the banks of the river, as shown in Figure 14. Deflections were accordingly measured using such a technique. In Figure 15, a drone view of the bridge during a dynamic load test is shown. The locomotive travelling on top of the bridge at controlled speeds excited accordingly spans under study.

Figure 13. GB-InSAR during load testing.

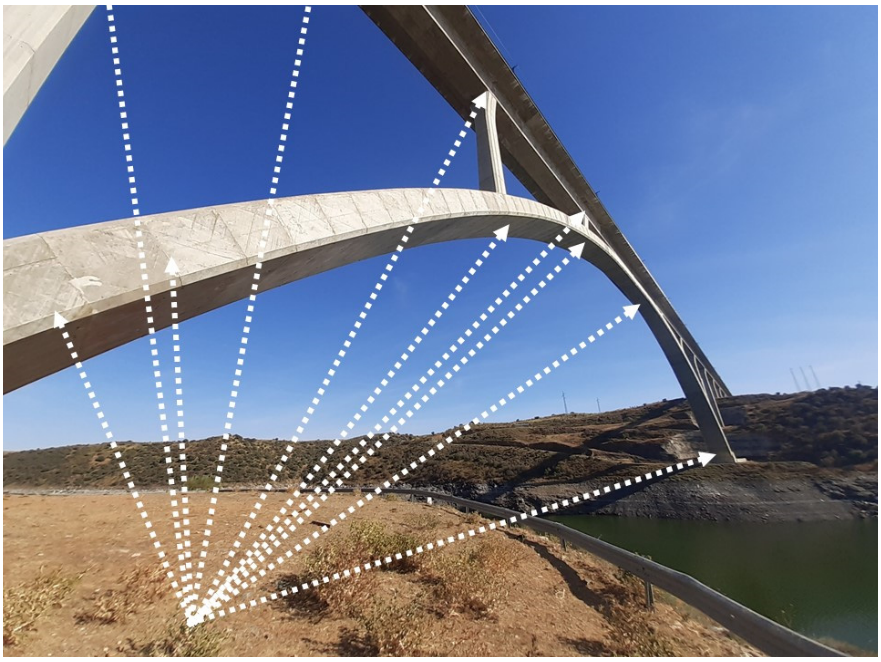


Figure 14. Location of GB-InSAR. Almonte Viaduct (arrows indicate waves sent to reflectometers).

Figure 15. View of the El Tajo Viaduct during the dynamic test.

3.1.3. Results and Discussion

This investigation presents the implementation of interferometer radar measurements to assess the displacements of arches and the deck during routine static and dynamic load tests. The considerable size of the arches and their significant height above the reservoir presented substantial challenges in acquiring accurate field data. Additionally, ground-based measurements were conducted during the dynamic tests, providing supplementary data for integration with accelerations collected using MEMS devices. The results derived from these measurements show the feasibility of using remote sensing techniques in bridge proof-testing. In future monitoring sessions of similar infrastructures, these measurements and their analyses can be incorporated into structural assessments to enhance their accuracy and reliability. To maximize accuracy, it is important to identify points of maximum reflectance. In environments with low electromagnetic noise, these points correspond to those with peak reflectance values. In this case study, in both static and dynamic tests, submillimeter accuracy was achieved. Low electromagnetic interference and favorable atmospheric conditions further enhance the precision of measurements, allowing for more reliable results, particularly in high-resolution applications such as bridge load testing.

3.2. Highway Bridge in Barcelona (TLS)

This is a case study showing the capabilities of remote sensing of bridges that are difficult to access.

3.2.1. Identification and Description of the Case Study

Numerous steel–concrete composite bridges are currently in operation, offering efficient and cost-effective structural solutions by leveraging the strengths of both concrete and steel. Typically, these bridges feature concrete slabs supported by steel plates or box girders. The beams in these structures often consist of welded steel plates with transverse and longitudinal stiffeners designed to optimize material usage, weight, and cost. However, this design can result in slender steel plates that may buckle under certain stress levels, leading to out-of-plane deformation and compromising the bridge's structural integrity.

During the design phase, sophisticated numerical models are used to predict plate buckling and other instability-related phenomena. Theoretical assumptions about initial imperfections of steel plates are considered before construction. However, the "as-built" shape of the plates is rarely used to verify these assumptions post-construction, and their evolution over time is not monitored. Consequently, the potential insights from the as-built models are currently overlooked. Obtaining such shapes using conventional methods at the bridge scale is an overwhelming task, requiring precise geometrical assessments. This case study uses a composite bridge in the Metropolitan Area of Barcelona to explore the feasibility of continuous geometric evaluations for structural assessment using TLS (Terrestrial Laser Scanning).

The PR-04-B015 bridge, located in the national highway network surrounding the Metropolitan Area of Barcelona (Spain), links two of the major highways in the network—the AP-7 Highway (heading North) and the A-2 Road (Heading West). This bridge is a crucial link between these two highways and offers users a bypass option to avoid driving through the suburbs of the metropolitan area while transitioning from north-south to east-west corridors or vice versa (Figure 16). As a result, it has become a vital asset for the transportation of goods from Catalonia to Northern Europe, especially for the movement of goods from the Barcelona port to other parts of Northern Europe.

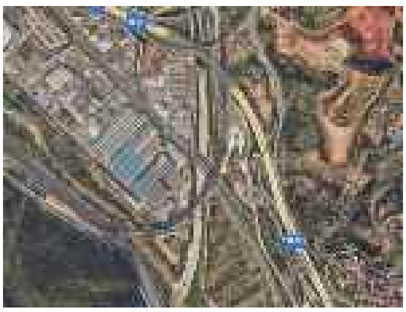


Figure 16. Plan view and view of Barcelona bridge.

The bridge was open to service in 2021. The bridge was accessible to researchers in the frame of the H2020 project ASHVIN (Assistants for Healthy, Safe, and Productive Virtual Construction Design, Operation & Maintenance using a Digital Twin), aimed at digitally twinning assets from the built environment. The bridge is relatively new and does not have any pathologies. However, fictional scenarios were set in order to establish information pipelines using different measuring techniques.

3.2.2. Selection and Description of the Remote Sensing Technique

One of the scenarios that was established was the existence of corrosion in the steel plates. This scenario led to the question of how much the load-bearing capacity of the bridge could be affected under these conditions. In order to deploy more realistic numerical predictions, the plates were modeled using their real shapes rather than Eigenvalue-based assumed shapes.

The point clouds of the imperfect plates are linked to the geometrical entities of the perfect plates that define the bridge. These imperfect plates are referred to as "as-built" plates. The measurements were deployed seasonally to ascertain the effect of the environmental conditions.

The bridge's original design project was completed several years ago, at a time when digital tools and BIM were not as advanced as they are now. The majority of the bridge's information was stored in PDF files, including all relevant information in the form of deliverables and 2D drawings. The corresponding development of the BIM model adhered to the IFC open standard, which, in its latest release, allows for the modeling of bridge components assigned with geometric representations, physical properties, and supplementary semantic information. The developed model includes comprehensive representations of the bridge's plates, slabs, piles, and stiffeners, as seen in Figure 17. This model was built using Rhinoceros v7 and Grasshopper, whereas the IFC was developed using BlenderBIM 4.2.3.

3.2.3. Results and Discussion

The bridge was scanned seasonally with different sun radiation and temperature conditions. Per episode, two scans from different viewpoints were conducted on a specific portion of the bridge. Replicability was ensured using spheres with fixed positions in all scans.

A total of six measuring episodes were conducted. The first scan was taken in March 2022, and the last in May 2023 (covering a year). The model and the initial scanned point cloud were co-registered using the Iterative Closest Points (ICP) algorithm.

The digital twin of the bridge can be systematically updated with new measurement information through an automated process that links the as-built point cloud data with the as-designed geometry in the model. This process enables individual linking of global and local levels of information.

The digital twin of the bridge was systematically updated with new measurement information through an automated process that links the as-built point cloud data with the as-designed geometry in the model. This process enables individual linking of global and local levels of information. Figure 18 shows a view of different steel plates of the cross-section (webs, flanges, diaphragms, stiffeners) and the corresponding point clouds of a given plate (web) with four different imperfect shapes (M1–M4). Nonlinear analyses considering imperfections can thus be fed using these realistic shapes.

The imperfect geometries were systematically treated in Grasshopper in order to perform several sensitive analyses (Figure 19) as well as to export these geometries to structural Software with GMNIA capabilities (nonlinear analysis with imperfections).

3.3. Colle Isarco Viaduct in Italy (Satellite InSAR)

The main advantages, but also the remaining difficulties, in the application of satellite remote sensing to bridges are described in this case study.

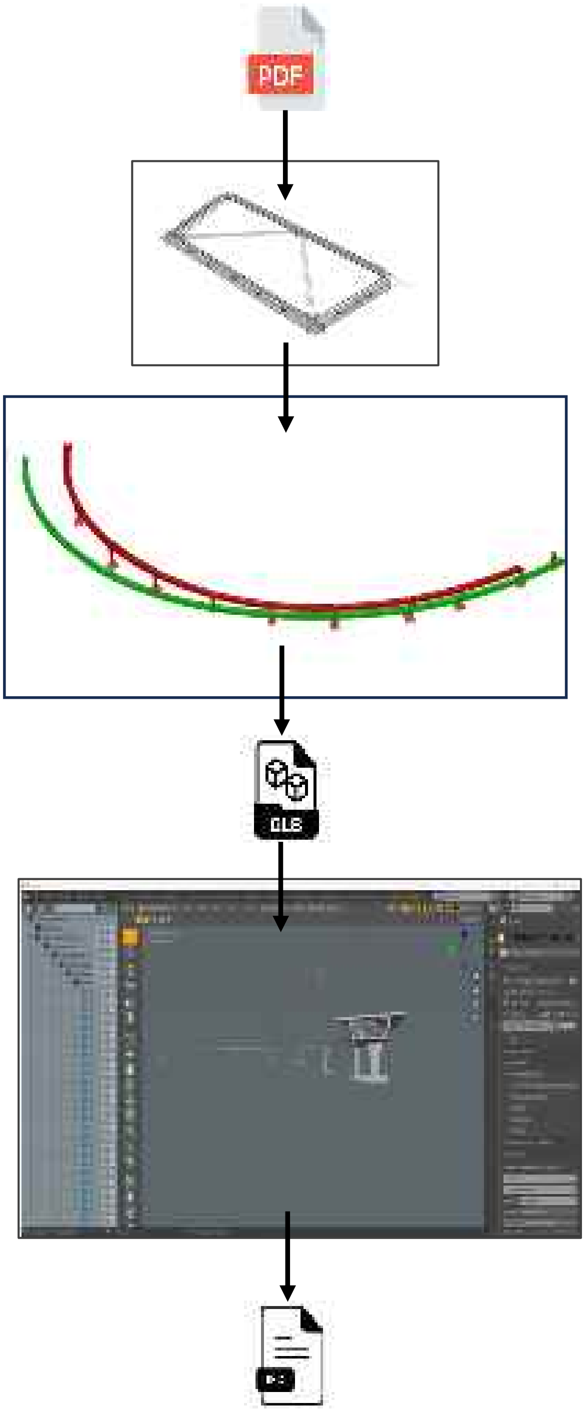


Figure 17. From PDF to IFC.

3.3.1. Identification and Description of the Case Study

The Colle Isarco Viaduct is a critical infrastructure within the European road network. Constructed primarily of prestressed concrete, this viaduct is part of the Italian Highway A22 and was erected in 1968. It consists of two structurally independent decks with 13 spans, totaling a length of 1028.2 m. The viaduct's main span, measuring 163 m, features symmetric prestressed concrete Niagara box girders supporting a suspended beam (Figure 20). Over the years, the Colle Isarco Viaduct has shown signs of high structural deformation, making it a subject of interest for monitoring and analysis.

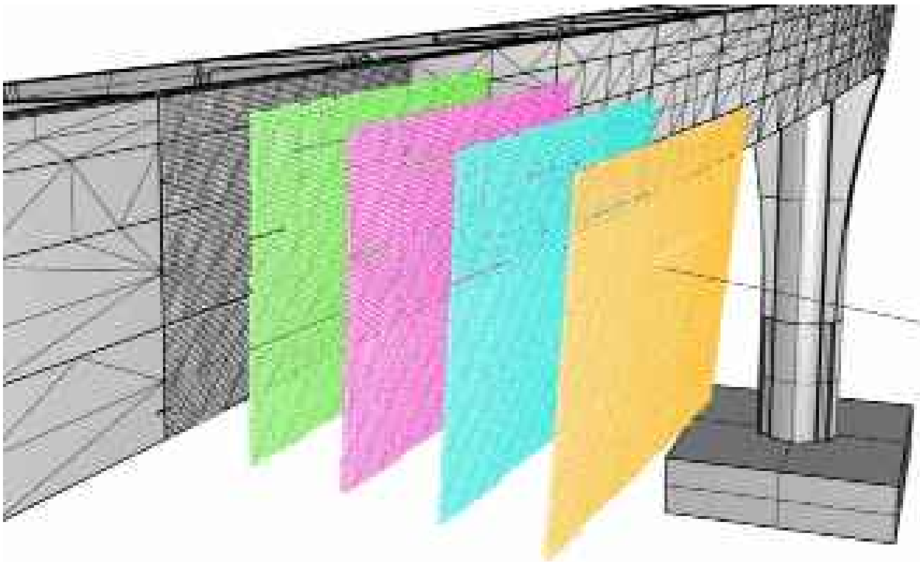


Figure 18. Seasonal imperfect web plates of a given sector.

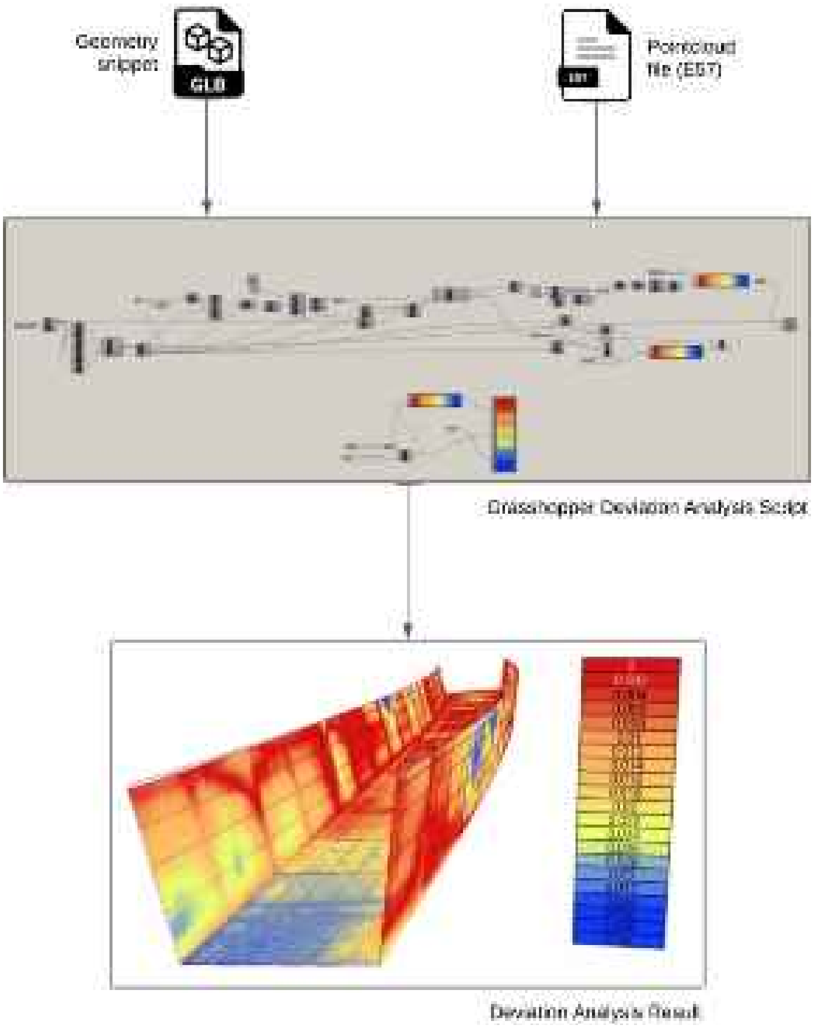


Figure 19. Analysis of imperfect plates using Grasshopper.

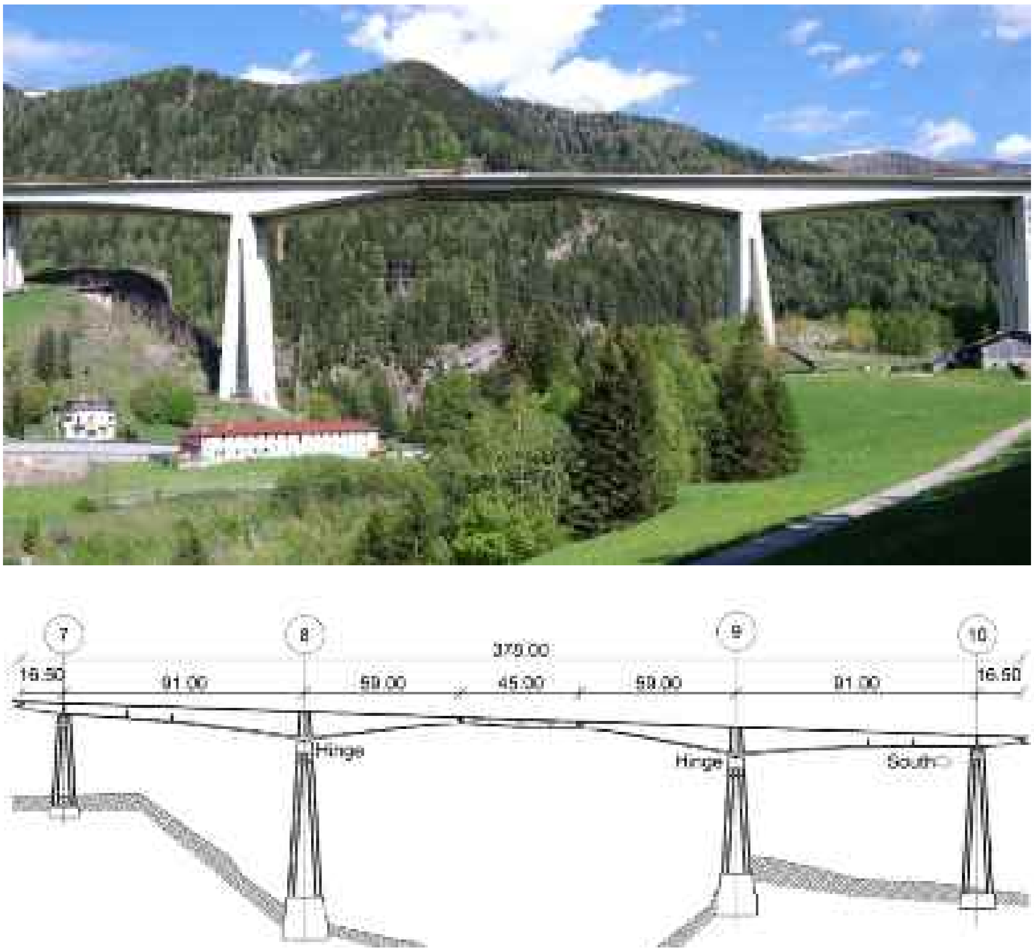


Figure 20. Main span of the Colle Isarco Viaduct.

This case study aims to assess the viability and accuracy of satellite InSAR in monitoring such large civil engineering structures, comparing it with conventional topographic monitoring methods. The study spans a period of four years, during which both InSAR and topographic data were collected and analyzed. Specifically, the viaduct's structural behavior was monitored using a topographic monitoring system consisting of two Leica Nova TM50 topographic total stations, which measure the displacements of 72 optical prisms GPR112 installed along the main span and in the surrounding area. This system's measurements served as the ground truth for comparing the satellite-based InSAR measurements.

3.3.2. Selection and Description of the Best Remote Sensing Technique

For this study, the SAR data from the COSMO-SkyMed satellite constellation, courtesy of the Italian Space Agency, were used. This constellation employs an X-band radar sensor, ideal for capturing mm-scale deformations. For the Colle Isarco Viaduct, a total of 62 SAR images were acquired in the X-band Stripmap Mode over a four-year period (2016–2020). These images were collected in the descending orbit to ensure optimal coverage and perspective of the viaduct, considering its mountainous location and alignment.

InSAR data processing using the Multi-Temporal InSAR (MT-InSAR) technique was conducted, extracting over 600 PSs along the bridge, each providing its displacement time series along the satellite's LoS. The temporal coherence (γ) of these PSs varied across different sections of the bridge, influencing the accuracy of displacement measurements (Figure 21). This variability in coherence was a critical factor in assessing the applicability and reliability of InSAR data for monitoring the structural health of the viaduct. We carried out the MT-InSAR data processing and analysis using SARproZ®, a specialized software for advanced InSAR data processing. This software enabled the extraction of detailed displacement time series from the PSs, which were then compared with the on-site topographic measurements to validate the accuracy and effectiveness of the InSAR technique in monitoring the structural behavior of the Colle Isarco Viaduct.

Figure 21. 3D distribution of the PSs extracted over the Colle Isarco Viaduct. Color scale: temporal coherence.

3.3.3. Results and Discussion

The comparison of the InSAR and topographic data for the Colle Isarco Viaduct over a four-year period yielded significant insights (Figure 22). The InSAR technology demonstrated a high degree of accuracy in areas with high temporal coherence of PSs. Specifically, the study observed a Root Mean Square Error (RMSE) of less than 3 mm and a Pearson linear correlation coefficient above 0.85 in these areas, indicating a strong agreement with the topographic measurements. However, challenges were evident in regions of the viaduct experiencing higher displacements, particularly at the cantilever ends, where the temporal coherence of PS was lower. Initially, the RMSE in these areas exceeded 6 mm, with a Pearson correlation coefficient below 0.4. The application of data fusion methods with topographic measurements significantly improved the accuracy, reducing the RMSE to below 4.6 mm and increasing the correlation coefficient to above 0.8.

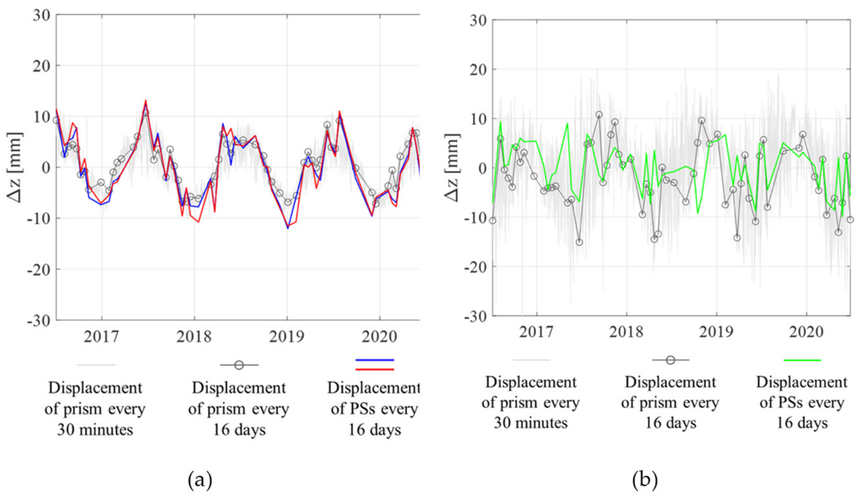


Figure 22. Comparison of vertical displacement time series from the topographic system's optical prisms and nearby PSs on the bridge. (**a**) Areas with high temporal coherence ($\gamma > 0.75$), and (**b**) areas with low temporal coherence ($\gamma < 0.3$).

These findings underscore the potential of InSAR as a standalone monitoring solution in areas with high-quality PS data. Nevertheless, the necessity for a hybrid monitoring approach combining InSAR with traditional methods is evident in areas with lower temporal coherence. This study highlights the importance of selecting appropriate monitoring techniques based on the specific characteristics of the infrastructure and its surroundings [48].

3.4. Truss Bridges in Portugal and Spain (Fully Automated: Scan-to-BIM & Scan-to-FEM)

Truss-type bridges are challenging structural typologies when they are already built and have been subjected to deterioration processes for a long time. The very first step to address when modeling an existing bridge is to develop its geometrical model, which, in accordance with previous sections, needs to be integrable in BIM-based management platforms, e.g., converting the generated model into an interoperable information model.

This case study demonstrates the feasibility of adopting the scan-to-BIM technology by combining terrestrial laser scanning data, automated data processing for semantic and instance segmentation using both heuristic and Machine Learning techniques, and finally, extracting relevant features to represent the geometrical reality of the bridge structure using IFC-compliant models and structural graph models fully compatible with FEM-based analysis software. This entire approach has developed in the context of the EU-funded SAFEWAY project [170] by the Applied Geotechnologies Research group at the University of Vigo, which published a compilation of papers addressing semantic and instance segmentation of truss-type bridges using a heuristic approach [39] and the automatic generation of IFC-compliant geometric and structural models [40]. In later research, the same group proposed a new method using Deep Learning models, aiming at increasing the generalization capability of the point cloud segmentation so it can be applied to any truss typology [171].

3.4.1. Identification and Description of the Case Study

The case study of this paper is the Dom Luis I Bridge in Santarem (Portugal), also known as the Bridge of Santarem. This bridge is on the Portugal national road 114 and crosses the Tagus River, joining Santarem and Almeirim. It was inaugurated in 1881, being by that time one of the largest civil work structures, the third-largest in Europe and the sixth-largest in the world [172].

The bridge is 1214 m long, and it is divided into two distinct parts with different structures. Only one part of the bridge is surveyed in the aforementioned project, consisting of a 594 m long truss beam structure resting on 11 pillars. For the demonstration of the automated processing of the point cloud and subsequent geometric modeling, one of the spans is subjected to the automated processing pipeline presented below. Figure 23 depicts the surveying works in the bridge with both TLS FARO Focus and the total station.

Figure 23. A general view of the Dom Luis I bridge during the data acquisition work: terrestrial laser scanning (**left picture**) and total station (**right picture**).

3.4.2. Selection and Description of the Best Remote Sensing Technique

As the purpose of this case study is to produce an accurate geometric model that represents the actual reality of the bridge, terrestrial laser scanning is proposed as the most suitable technique. Even though the automated processing pipeline explained can deal with point clouds generated from different sources, namely, LiDAR-based systems or image-based photogrammetric methods, TLS has been selected due to four main reasons:

(i) accuracy of the collected points, whose nominal error in distance measurement is in the range of millimeters; (ii) density of measurements, which in overall terms, allows for points spaced between 5 mm in closer areas to the scanner position, and 15 mm in zones further from the scanner station; (iii) simplicity of the pre-processing, as the most primitive geometric model in the form of point clouds, can be obtained directly from the scanner whilst in photogrammetric-based solutions the dense point cloud can only be obtained after inner and exterior orientation of the images using specific software; and (iv) the quality of the measurements is much less sensitive to environmental conditions, especially in the case of images which are severely constrained by lighting.

Considering the points mentioned above, the in situ survey consisted of the acquisition of dense point clouds using a TLS FARO Focus X330, supported by a topographic survey to accurately measure control points using a TLS Leica TS15.

The TLS used is a phase-shift laser scanner that has an operating range of 0.6–120 m and a nominal accuracy of $\pm$2 mm at 25 m distance in normal reflectivity and illumination conditions. The field of view of this instrument covers 360 degrees in the horizontal field and 305 degrees in the vertical plane. The maximum angular resolution of this scanner is 0.009 degrees, and the acquisition rate reaches up to one million points per second when working at maximum speed.

Due to the restricted access to the structure, multiple scanner stations were needed from both riversides. This network was formed by 18 different scanner positions, providing a total of 37 scans, to ensure that the bridge structure was recorded. The data collection from each scanner position consisted of (1) a low-resolution scan, with the aim of having a draft panorama view where to identify the placement of the structure to be scanned in detail; (2) a high-resolution scan of the field of view corresponding to the bridge; (3) this high-resolution scan was completed with the recording of RGB images in order to texturize the acquired point clouds, even though the color attribute is not strictly needed for geometric purposes.

In parallel to the scanning works, a robotic total station was used to accurately acquire the coordinates of a net of control points (527 points) with a double purpose: to ensure that all the scans can be aligned robustly using known targets and to set reference points for multi-temporal surveys in such a waypoint clouds collected in different epochs can solidly register the same coordinate system.

Once all scanners were downloaded, they were all aligned to the same coordinate system using the control points measured during the topographic survey, composing the bridge's point cloud as depicted in Figure 24. This produced a global consolidated point cloud comprising more than 100 million points, with an overall RSME of 11 mm. As mentioned above, the spacing among adjacent points ranged from 5 to 15 cm depending on the point's distance to the scanner's position, but after overlapping the scans collected from the different placements, the density was significantly increased, leading to a heavy global point cloud with redundancies that did not contribute to defining geometric details below 1 cm. To light this point cloud and reduce the redundant point, filtering operations were applied in such a way the maximum spatial resolution was 5 mm. Despite the size of the point cloud, the complexity of the truss beam often provokes occlusions to almost all the elements of the beam, especially in the bars of the inner parts.

3.4.3. Results and Discussion

In [39], the authors propose a heuristic approach to automatically segment the point cloud into individual bars composing the truss beam. Their overall strategy consisted of applying a sequence of operations that downsample and add topologic attributes to the points so they can be classified following logic rules. These operations are applied to each main plane of the truss bridge, namely the vertical faces, bottom faces, and inner Saint Andrew's crosses. Figure 25 depicts the overall strategy applied so that the consolidated point cloud can be partitioned into smaller point clouds that represent each bar. The first step consists of calculating the main orientation of the bridge point cloud using a Principal Component Analysis (PCA), so a conformal transformation is applied to the point cloud in such a way the separation of the face's points is straightforward using thresholding to each coordinate. The next step consists of a voxelization that down-samples the face point cloud, and new attributes for each voxel are calculated using the points contained in each voxel space. Among these new attributes, a dimensional analysis becomes very useful using the eigenvalues of a PCA computed for the points of each voxel. This means that points can be labeled as linear, planar, or volumetric. Also, the outputs of the PCA analysis at the voxel level add relevant information about the point's normals. Thus, with this information, the point can not only be classified as vertical or horizontal but can also establish thresholds that help classify points according to their orientation.

Figure 24. Consolidated point cloud of Dom Luis I Bridge: illustration of different scans (each with a different color) in the top left image; illustration of the consolidated point cloud colored using intensity attribute (bottom left image); and portion of the point cloud where many occlusions provoke that the bars are incomplete.

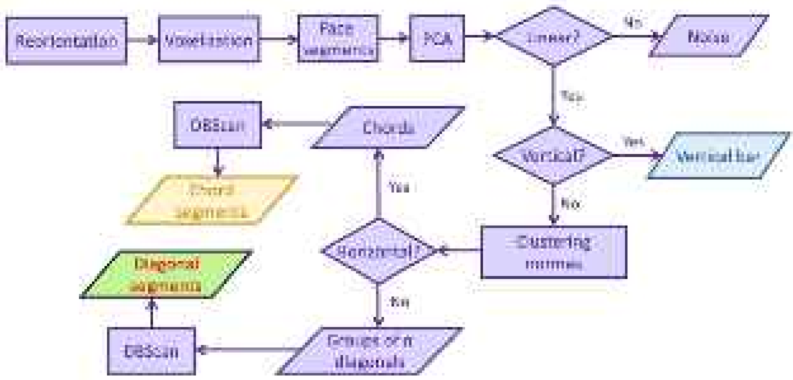


Figure 25. Workflow for heuristic semantic segmentation of truss-type bridges [39].

After the points are semantically segmented, a density-based clustering algorithm is applied within each class so that the resulting subsets of points correspond to each individual bar composing the truss.

It must be noted that the result of this phase is still a point cloud, and occlusions are still present. Thus, the model is not yet exploitable for BIM-based applications. For that reason, the next phase of this project consisted of developing a methodology for the automated conversion of these segmented point clouds into complete geometric models compliant with IFC standards and, subsequently, a structural graph that can be imported and edited in FEM-based analysis software.

Justo et al. [40] presented a methodology that performs the required modeling starting with the segmented point clouds obtained in the previous phase. One of the challenges of this modeling is to deal with the occlusion or largely incomplete point clouds of every truss bar, so the authors propose to use a bounding box of each subset of points to guide the geometric modeling. The proposed methodology is summarized in the flowchart presented in Figure 26, and overall, it comprises three main steps:

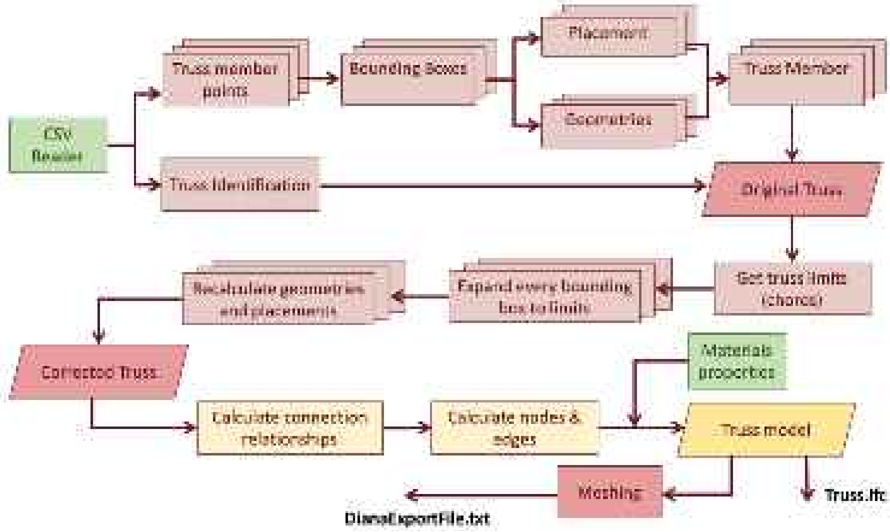


Figure 26. Workflow for the geometric reconstruction of the truss beam from 3D point clouds [40].

The first step consists of creating a bounding box for each set of points, considering that, in many cases, it does not entirely cover the real dimensions of truss bars due to the point cloud occlusions mentioned above (Figure 27C). For that reason, Step 2 consists of an extension of the bounding box along the principal direction, assuming as delimiters of this extension some other bars of the structure; in this case, the delimiters are the chords and the vertical posts at both ends of the truss (Figure 27D). Finally, once the bounding boxes have been refined and geometrically represent truss bars, the final step consists of the establishment of the connections among truss members to analyze the intersections among bars and thus detect the nodes and the edges for the structural graph as depicted in Figure 27E. After the reconstruction had been completed, the parameters for this model were exported to BIM using IFC v4.1. This version of the IFC schema was selected due to the limited number of programming libraries at the time of the project. However, the development considered the existing documentation about IFC 4.3 with the purpose of making the tool fully compatible with the forthcoming IFC versions.

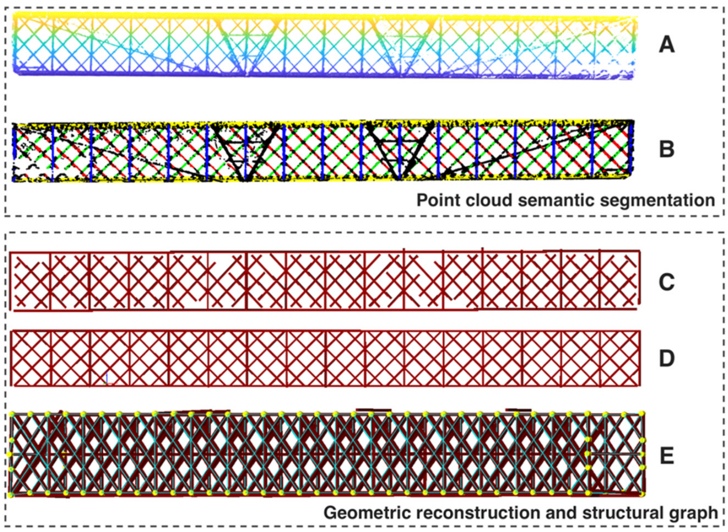


Figure 27. Generation of the IFC model and structural graph from point clouds: original point cloud of one of the truss faces (**A**); segmented point cloud according to the type of bar in the truss beam (**B**); first geometric reconstruction with bounding boxes for each segmented bar (**C**); corrected geometric model after extrusion and collision of bars (**D**); and structural graph after identifying nodes (yellow dots) and edges (blue lines) (**E**).

3.5. Virtual Reality (VR)

The VR tool has been mostly used for collaborative multi-user platforms to reduce site visits and inspections [110], enabling a remote site visit and inspection platform for the inspectors, engineers, and other parties, allowing them to join from their offices (Figure 28). On the other hand, AR and MR have been generally utilized for reducing human labor, hence subjectivity in the field by assisting the inspectors or engineers with digital virtual visual aids in the head-mounted display for detecting and measuring defect size in the structure, improving the inspector's work efficiency as outlined in Figure 29 [112].

Figure 28. The collaborative multi-user VR environment (Reprinted with permission from Ref. [164], 2022, Elsevier).

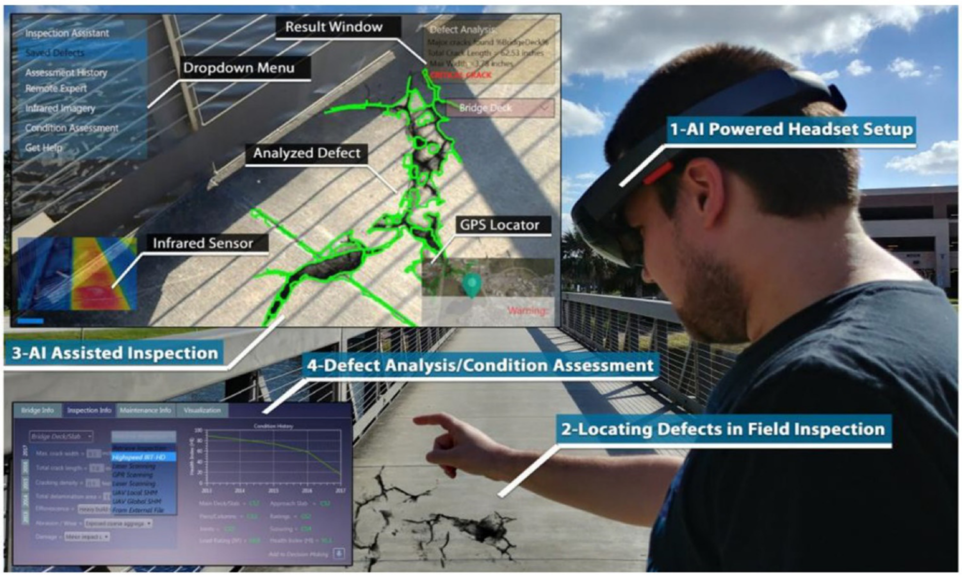


Figure 29. AI-guided field inspection using HoloLens (Reprinted with permission from Ref. [112], 2019, SAGE).

In a notable case study [173], a groundbreaking approach was introduced for data fusion in the condition assessment of bridges. This innovative method leverages VR technology and approaches, integrating dynamic monitoring sensor data with visual data collected from bridge structures. Specifically, the magnitude and phase values of mode shape vectors, derived from the bridge's acceleration monitoring datasets, are fused with the spatial coordinates of the bridge's LiDAR-based point cloud data. This data fusion approach, named ModeShapeFuser (Figure 30), enables the visualization of mode shapes of engineering structures within their point cloud. This offers a model with higher spatial resolution, enhancing the understanding of the dynamic behaviors of existing structures. The authors demonstrated this method in a case study on a bridge, showcasing how this immersive data visualization technique, utilizing VR, can provide a more intuitive and comprehensive understanding of the dynamic behavior characteristics of bridges.

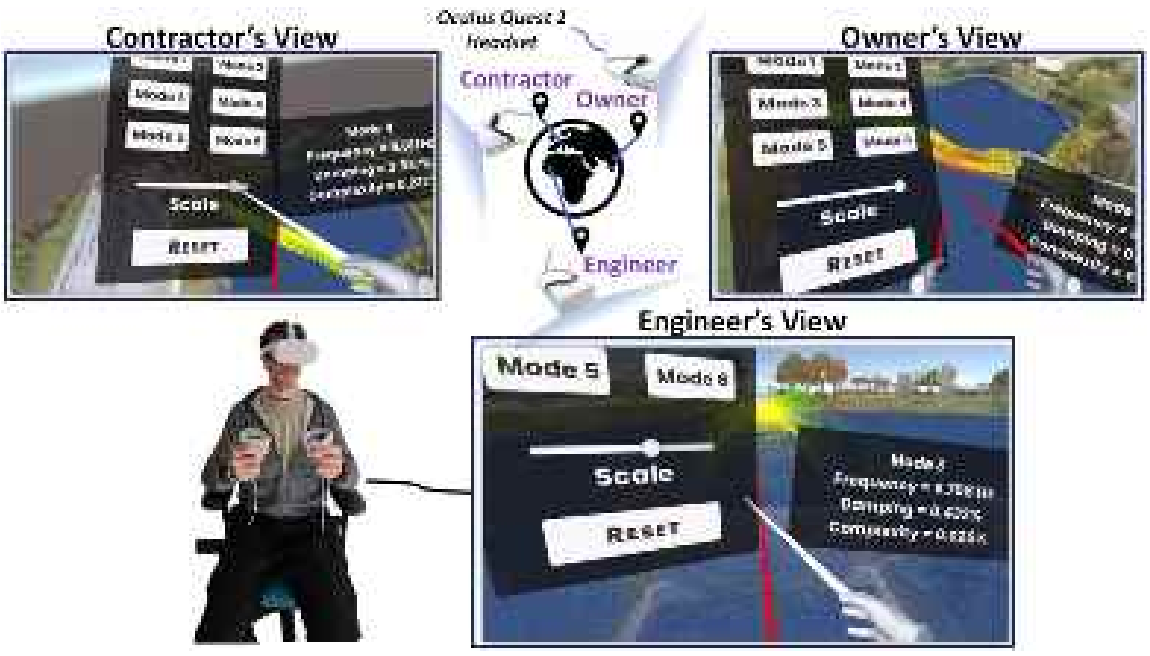


Figure 30. The multi-user VR environment shows the ModeShapeFuser methodology (Reprinted with permission from Ref. [173], 2024, Elsevier).

This ModeShapeFuser immersive visualization, used in the VR environment, allows for a virtual tour of the bridge in its actual environment and enables a collaborative setting for decision-makers. The study underscores the importance of this method in informed decision-making processes regarding the assessment of existing bridges and other engineering infrastructure systems, with implications for their construction, operation, maintenance, and safety.

In another study by Luleci and Catbas [174], the authors introduced a Virtual Meeting Environment (VME) leveraging VR to assess its impact on decision-making. VME essentially includes several structural monitoring data, models, and structure legacy data coupled with immersive visualization techniques, such as the ModeShapeFuser (Figure 31). In their study, practicing engineers participated in experiments using VME, followed by a questionnaire to gather feedback on VME's efficiency. The questionnaire results were used to inform the meeting functions in the Inspection Simulation Environment (ISE), which simulates bridge inspections through agents in various meeting settings. Decision-making results from these simulations were analyzed to understand VME's impact on infrastructure inspections, with insights from practicing engineers providing practical considerations. The questionnaire results revealed that 91% of the engineers believe VME enhances meeting efficiency and aids in decision-making during inspections. The simulation results indicated that using VME, in conjunction with current practices, improves decision-making. This improvement is even more significant when compared to solely on-site meetings. The study also found that the reliability of data tools further enhances VME's positive impact on decision-making.

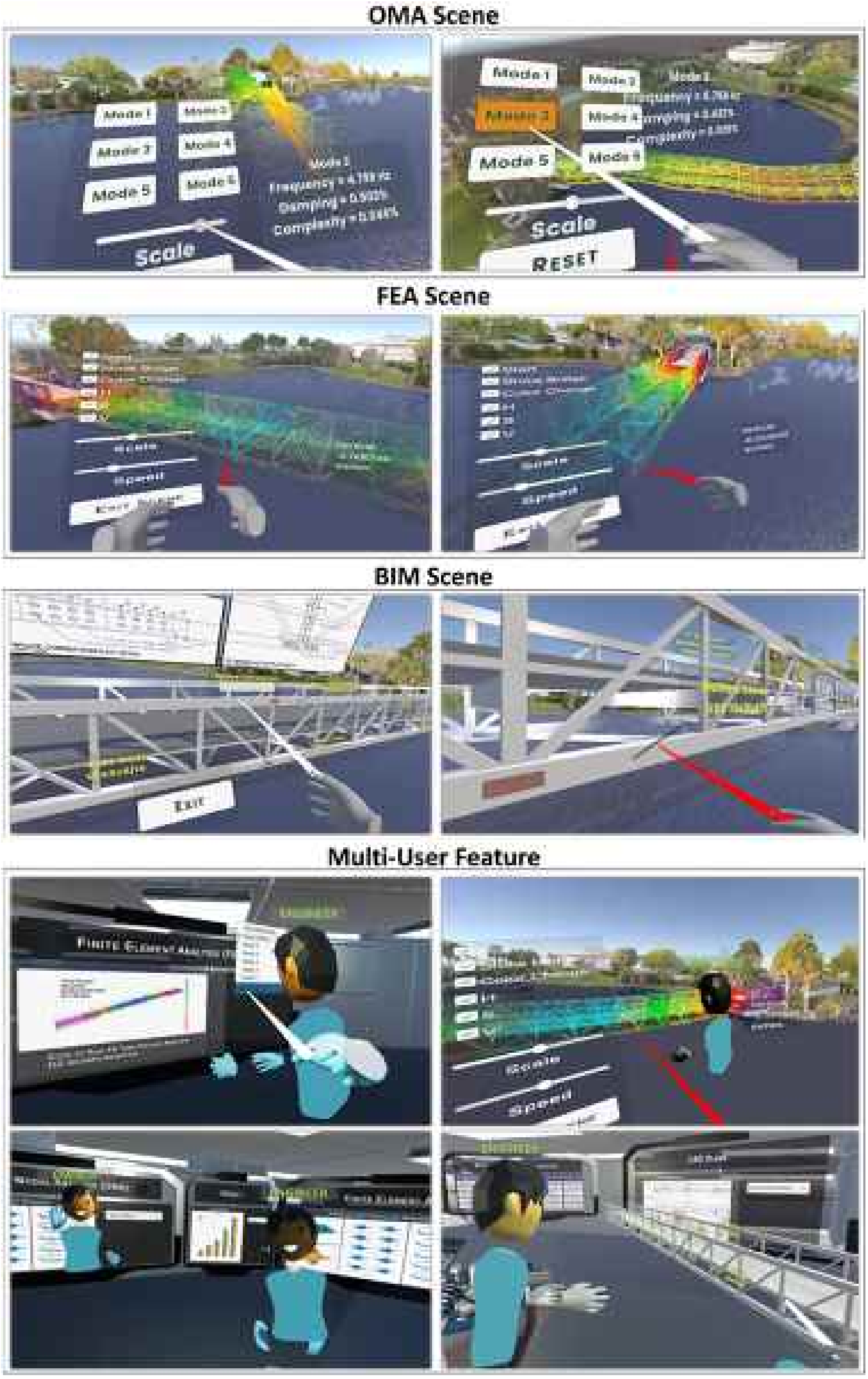


Figure 31. Some of the different infrastructure data and models are presented in this collaborative multi-user VME (Reprinted with permission from Ref. [174], 2024, Elsevier).

4. Conclusions

This review paper presented a transversal view of the diverse remote sensing technologies that have shown successful applications for the digitalization of existing bridges, showing their practical capabilities in collecting relevant information for informed decision-making processes. The following conclusions can be summarized from the review of many applications worldwide to bridge monitoring and from the presented case studies.

Laser scanning is used both in the creation of structural models of the bridge and for the SHM of operating bridges. In the creation of structural models from laser scanning data, it is common to integrate the scanning data with other non-destructive data to assess not only the external geometry but also internal properties very relevant to the structural response of the bridge. In relation to SHM, there is a vast body of literature reporting works dealing with the detection of cracks, monitoring deformation, automated detection of defects, and changes in the structure over time. Terrestrial Laser Scanners require considerably high data-gathering capabilities. Successive scans performed in time may provide great value for the performance of the bridge asset. Replicability is of great importance. Proper registration methods for spatial location and reference to the point clouds are required.

InSAR technology has shown great promise for large-scale monitoring and bridge failure prevention. The future of InSAR in bridge monitoring is promising but not without challenges. The method has been shown to be very effective in the monitoring of subsidence and landslides, which results in high applicability to problems related to scouring of the foundations or deep movements in the foundations of abutments. However, the accuracy of InSAR in capturing these movements can be influenced by factors such as the orientation of the bridge relative to the satellite's line of sight. This highlights the importance of considering the geometrical relationship between the bridge and the satellite in the planning and interpretation of InSAR data. The need for improved data processing techniques, particularly for handling complex topographical settings, remains a significant hurdle. Moreover, the integration of InSAR with other remote sensing technologies could lead to a more holistic approach to infrastructure monitoring. The potential of InSAR to revolutionize SHM is clear; the integration of this data with machine learning represents an innovative approach to managing the vast amount of data generated, enabling more efficient analysis and interpretation. However, for InSAR to be fully integrated into standard SHM practices, ongoing research and development are essential. This includes exploring advanced data processing algorithms, enhancing satellite sensor capabilities, and establishing standardized protocols for data interpretation and integration with traditional monitoring methods.

Terrestrial photogrammetry has also been considered for the creation of structural models of existing bridges, especially relevant to the case of masonry arch bridges where actual geometry is important and related to their structural stability.

Extended Reality in the form of VR, AR, and MR tools have been extensively used for structural condition assessment of bridges. These techniques can be fully and easily implemented into the actual standard visual inspection protocols, which are still the most used by bridge owners. This may facilitate the incorporation of these remote sensing technologies in the bridge management policies.

GNSS stations are already present in bridge monitoring applications, mainly for the determination of reference points for other sensors or to transfer optical or topometric data to a specific reference frame, but rarely as an acquisition tool itself. Over the last decade, with the ever-increasing performance of GNSS hardware, several studies have assessed the performance of GNSS for dynamic monitoring, and their application in the monitoring of long-span bridges has been a subject of increasing interest and research.

Remote sensing offers a flexible alternative to permanent Structural Health Monitoring (SHM) systems, reducing the need for continuous sensor installations and ongoing maintenance. Permanent SHM systems require substantial investment in equipment, sensor upkeep, and dedicated personnel for operation, driving up long-term costs. In contrast, remote sensing can be deployed on an as-needed basis, significantly lowering these expenses by minimizing permanent installations. Additionally, remote sensing can complement a sparser permanent SHM system, providing enhanced monitoring capabilities where fixed sensors may be limited, offering a cost-effective solution while maintaining comprehensive coverage.

Remote sensing techniques stand apart from traditional measurement methods due to their inherently unstructured and complex data formats, which often involve spatial, spectral, and temporal dimensions. Unlike the conventional, straightforward time-series data generated by many sensor-based systems, remote sensing data require advanced processing, interpretation, and integration techniques to unlock valuable insights. This distinction underscores the need for specialized tools and approaches to effectively handle and analyze remote sensing information.

In summary, remote sensing applied to bridge engineering has shown its capability to overcome and solve problems encountered when using traditional contact sensors for bridge health monitoring due to access difficulties to some parts of the bridge or because global performance is of interest more than local behavior. In this sense, remote sensing of bridges can be seen to include useful and broad methods and technologies, now and in the future, for the management of the existing bridge stock.

Funding: Part of the research and case studies presented here was supported by the U.S. National Science Foundation (NSF) Division of Civil, Mechanical, and Manufacturing Innovation (Grant Number 1463493), Transportation Research Board of the National Academies-IDEA Project 222, and National Aeronautics and Space Administration (NASA) Award No. 80NSSC 20K0326, by the European Commission through the ASHVIN project: "Assistants for Healthy, Safe, and Productive Virtual Construction Design, Operation & Maintenance using a Digital Twin" an H2020 project under agreement 958161 and by Grant PID2021-126405OB-C31 funded by MCIN/AEI/10.13039/501100011033 and by "ERDF A way of making Europe". The work has also received support from the MONITORED project, Ref. RED2022-134431-T funded by MCIN/AEI/10.13039/501100011033. This research was also financed by the European Union-Next Generation EU, Mission 4 Component 2-CUP E53D23003560006. The study presented was also carried out as part of the program of activities carried out as part of the agreement between the ReLUIS Interuniversity Consortium and the Superior Council of Public Works stipulated pursuant to art. 3 of the Decree of the Minister of Infrastructure no. 578 of 17 December 2020, and the agreement between the ReLUIS Interuniversity Consortium and the Italian Department of Civil Protection. COSMO-SkyMed products have been provided free of charge for research purposes by the Italian Space Agency, Project Card ID: 630 "SAR SHM of bridges".

Data Availability Statement: The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Pregnolato, M.; Gunner, S.; Voyagaki, E.; De Risi, R.; Carhart, N.; Gavriel, G.; Tully, P.; Tryfonas, T.; Macdonald, J.; Taylor, C. Towards Civil Engineering 4.0: Concept, Workflow and Application of Digital Twins for Existing Infrastructure. *Autom. Constr.* **2022**, *141*, 104421. [CrossRef]
2. Torzoni, M.; Tezzele, M.; Mariani, S.; Manzoni, A.; Willcox, K.E. A Digital Twin Framework for Civil Engineering Structures. *Comput. Methods Appl. Mech. Eng.* **2024**, *418*, 116584. [CrossRef]
3. Chacón, R.; Ramonell, C.; Posada, H.; Sierra, P.; Tomar, R.; Martínez de la Rosa, C.; Rodriguez, A.; Koulalis, I.; Ioannidis, K.; Wagmeister, S. Digital Twinning during Load Tests of Railway Bridges—Case Study: The High-Speed Railway Network, Extremadura, Spain. *Struct. Infrastruct. Eng.* **2023**, *20*, 1105–1119. [CrossRef]
4. Bado, M.F.; Tonelli, D.; Poli, F.; Zonta, D.; Casas, J.R. Digital Twin for Civil Engineering Systems: An Exploratory Review for Distributed Sensing Updating. *Sensors* **2022**, *22*, 3168. [CrossRef]
5. Strauss, A.; Matos, J.C.; Casas, J.R.; Fernandes, S. Quality Specifications and Performance Indicators for Road Bridges in Europe. In Proceedings of the IABSE Symposium, Guimaraes 2019: Towards a Resilient Built Environment Risk and Asset Management—Report, Guimarães, Portugal, 27–29 March 2019.
6. Stipanovic, I.; Matos, J.C.; Casas, J.R.; Bukhsh, Z.A. Multiple Performance Goals in Bridge Management Systems—Overview of COST TU-1406 Results. In Proceedings of the ICRRR 2018, Cape Town, South Africa, 18–21 June 2018.
7. Casas, J.R.; Matos, J.C. Quality Specifications for Roadway Bridges, Standardization at a European Level. In *Risk-Based Bridge Engineering, Proceedings of the 10th New York City Bridge Conference, New York, NY, USA, 26–27 August 2019*; CRC Press: Boca Raton, FL, USA, 2019.

8. Puri, N.; Turkan, Y. Bridge Construction Progress Monitoring Using Lidar and 4D Design Models. *Autom. Constr.* **2020**, *109*, 102961. [CrossRef]
9. Vosselman, G.; Maas, H.-G. *Airborne and Terrestrial Laser Scanning*; Whittles Publishing: Dunbeath, UK, 2010; ISBN 978-1-904445-87-6.
10. Riveiro, B.; Lindenbergh, R. *Laser Scanning: An Emerging Technology in Structural Engineering*; Riveiro, B., Lindenbergh, R., Eds.; CRC Press/Balkema: Leiden, The Netherlands, 2019; ISBN 9781351018869.
11. Rashidi, M.; Mohammadi, M.; Sadeghlou Kivi, S.; Abdolvand, M.M.; Truong-Hong, L.; Samali, B. A Decade of Modern Bridge Monitoring Using Terrestrial Laser Scanning: Review and Future Directions. *Remote Sens.* **2020**, *12*, 3796. [CrossRef]
12. Riveiro, B.; Morer, P.; Arias, P.; de Arteaga, I. Terrestrial Laser Scanning and Limit Analysis of Masonry Arch Bridges. *Constr. Build. Mater.* **2011**, *25*, 1726–1735. [CrossRef]
13. Solla, M.; Riveiro, B.; Lorenzo, H.; Armesto, J. Ancient Stone Bridge Surveying by Ground-Penetrating Radar and Numerical Modeling Methods. *J. Bridge Eng.* **2014**, *19*, 110–119. [CrossRef]
14. Gordon, S.; Lichti, D.; Stewart, M.; Franke, J. Structural Deformation Measurement Using Terrestrial Laser Scanners. In Proceedings of the 11th FIG Symposium on Deformation Measurements, Santorini, Greece, 5–28 May 2003.
15. Zogg, H.-M.; Ingensand, H. Terrestrial Laser Scanning for Deformation Monitoring–Load Tests on the Felsenau Viaduct (CH). *Int. Arch. Photogr. Remote Sens.* **2008**, *37*, 555–562.
16. Berényi, A.; Lovas, T.; Barsi, Á.; Dunai, L. Potential of Terrestrial Laserscanning in Load Test Measurements of Bridges. *Period. Polytech. Civ. Eng.* **2009**, *53*, 25. [CrossRef]
17. Erdélyi, J.; Kopáčik, A.; Kyrinovič, P. Spatial Data Analysis for Deformation Monitoring of Bridge Structures. *Appl. Sci.* **2020**, *10*, 8731. [CrossRef]
18. Lõhmus, H.; Ellmann, A.; Märdla, S.; Idnurm, S. Terrestrial Laser Scanning for the Monitoring of Bridge Load Tests—Two Case Studies. *Surv. Rev.* **2017**, *50*, 270–284. [CrossRef]
19. Alamdari, M.M.; Ge, L.; Kildashti, K.; Zhou, Y.; Harvey, B.; Du, Z. Non-Contact Structural Health Monitoring of a Cable-Stayed Bridge: Case Study. *Struct. Infrastruct. Eng.* **2019**, *15*, 1119–1136. [CrossRef]
20. Truong-Hong, L.; Lindenbergh, R.; Nguyen, T.A. Structural Assessment Using Terrestrial Laser Scanning Point Clouds. *Int. J. Build. Path. Adaptat.* **2021**, *40*, 345–379. [CrossRef]
21. Riveiro, B.; Caamaño, J.C.; Arias, P.; Sanz, E. Photogrammetric 3D Modelling and Mechanical Analysis of Masonry Arches: An Approach Based on a Discontinuous Model of Voussoirs. *Autom. Constr.* **2011**, *20*, 380–388. [CrossRef]
22. Walsh, S.B.; Borello, D.J.; Guldur, B.; Hajjar, J.F. Data Processing of Point Clouds for Object Detection for Structural Engineering Applications. *Comput.-Aided Civ. Infrastruct. Eng.* **2013**, *28*, 495–508. [CrossRef]
23. Conde-Carnero, B.; Riveiro, B.; Arias, P.; Caamaño, J.C. Exploitation of Geometric Data Provided by Laser Scanning to Create FEM Structural Models of Bridges. *J. Perform. Constr. Facil.* **2016**, *30*, 04015053. [CrossRef]
24. Gyetvai, N.; Truong-Hong, L.; Laefer, D.F. Laser Scan-Based Structural Assessment of Wrought Iron Bridges: Guinness Bridge, Ireland. *Proc. Inst. Civ. Eng.-Eng. Hist. Herit.* **2018**, *171*, 76–89. [CrossRef]
25. Trias, A.; Yu, Y.; Gong, J.; Moon, F.L. Supporting Quantitative Structural Assessment of Highway Bridges through the Use of LiDAR Scanning. *Struct. Infrastruct. Eng.* **2021**, *18*, 824–835. [CrossRef]
26. Solla, M.; Lorenzo, H.; Novo, A.; Caamaño, J.C. Structural Analysis of the Roman Bibei Bridge (Spain) Based on GPR Data and Numerical Modelling. *Autom. Constr.* **2012**, *22*, 334–339. [CrossRef]
27. Conde, B.; Ramos, L.F.; Oliveira, D.V.; Riveiro, B.; Solla, M. Structural Assessment of Masonry Arch Bridges by Combination of Non-Destructive Testing Techniques and Three-Dimensional Numerical Modelling: Application to Vilanova Bridge. *Eng. Struct.* **2017**, *148*, 621–638. [CrossRef]
28. Oliveira, D.V.; Allahvirdizadeh, R.; Sánchez, A.; Riveiro, B.; Mendes, N.; Silva, R.A.; Fernandes, F. Structural Performance of a Medieval Stone Masonry Arch Bridge. In Proceedings of the IABSE Symposium, Wroclaw 2020: Synergy of Culture and Civil Engineering—History and Challenges, Report, Zurich, Switzerland, 7–9 October 2020.
29. Bouzas, O.; Conde, B.; Cabaleiro, M.; Riveiro, B. A Holistic Methodology for the Non-Destructive Experimental Characterization and Reliability-Based Structural Assessment of Historical Steel Bridges. *Eng. Struct.* **2022**, *270*, 114867. [CrossRef]
30. Kaartinen, E.; Dunphy, K.; Sadhu, A. LiDAR-Based Structural Health Monitoring: Applications in Civil Infrastructure Systems. *Sensors* **2022**, *22*, 4610. [CrossRef] [PubMed]
31. Valença, J.; Puente, I.; Júlio, E.; González-Jorge, H.; Arias-Sánchez, P. Assessment of Cracks on Concrete Bridges Using Image Processing Supported by Laser Scanning Survey. *Constr. Build. Mater.* **2017**, *146*, 668–678. [CrossRef]
32. Laefer, D.F.; Truong-Hong, L.; Carr, H.; Singh, M. Crack Detection Limits in Unit Based Masonry with Terrestrial Laser Scanning. *NDT E Int.* **2014**, *62*, 66–76. [CrossRef]
33. Cabaleiro, M.; Lindenbergh, R.; Gard, W.F.; Arias, P.; van de Kuilen, J.W.G. Algorithm for Automatic Detection and Analysis of Cracks in Timber Beams from LiDAR Data. *Constr. Build. Mater.* **2017**, *130*, 41–53. [CrossRef]
34. Riveiro, B.; DeJong, M.J.; Conde, B. Automated Processing of Large Point Clouds for Structural Health Monitoring of Masonry Arch Bridges. *Autom. Constr.* **2016**, *72*, 258–268. [CrossRef]
35. Jing, Y.; Sheil, B.; Acikgoz, S. Segmentation of Large-Scale Masonry Arch Bridge Point Clouds with a Synthetic Simulator and the BridgeNet Neural Network. *Autom. Constr.* **2022**, *142*, 104459. [CrossRef]
36. Truong-Hong, L.; Lindenbergh, R. Automatically Extracting Surfaces of Reinforced Concrete Bridges from Terrestrial Laser Scanning Point Clouds. *Autom. Constr.* **2022**, *135*, 104127. [CrossRef]

37. Kim, H.; Yoon, J.; Hong, J.; Sim, S.-H. Automated Damage Localization and Quantification in Concrete Bridges Using Point Cloud-Based Surface-Fitting Strategy. *J. Comput. Civ. Eng.* **2021**, *35*, 04021028. [CrossRef]
38. Sánchez-Rodríguez, A.; Riveiro, B.; Conde, B.; Soilán, M. Detection of Structural Faults in Piers of Masonry Arch Bridges through Automated Processing of Laser Scanning Data. *Struct. Control Health Monit.* **2017**, *25*, e2126. [CrossRef]
39. Lamas, D.; Justo, A.; Soilán, M.; Cabaleiro, M.; Riveiro, B. Instance and Semantic Segmentation of Point Clouds of Large Metallic Truss Bridges. *Autom. Constr.* **2023**, *151*, 104865. [CrossRef]
40. Justo, A.; Lamas, D.; Sánchez-Rodríguez, A.; Soilán, M.; Riveiro, B. Generating IFC-Compliant Models and Structural Graphs of Truss Bridges from Dense Point Clouds. *Autom. Constr.* **2023**, *149*, 104786. [CrossRef]
41. Zhou, Y.; Xiang, Z.; Zhang, X.; Wang, Y.; Han, D.; Ying, C. Mechanical State Inversion Method for Structural Performance Evaluation of Existing Suspension Bridges Using 3D Laser Scanning. *Comput. Civ. Infrastruct. Eng.* **2022**, *37*, 650–665. [CrossRef]
42. Ramonell, C.; Chacón, R.; Krenn, B.; Puig-Polo, C. Automated Pipeline for the Analysis of a Scale-reduced Steel Cable Net. *ce/papers* **2022**, *5*, 1060–1066. [CrossRef]
43. Hou, F.; Rui, X.; Fan, X.; Zhang, H. Review of GPR Activities in Civil Infrastructures: Data Analysis and Applications. *Remote Sens.* **2022**, *14*, 5972. [CrossRef]
44. Pieraccini, M.; Miccinesi, L.; Abdorazzagh Nejad, A.; Naderi Nejad Fard, A. Experimental Dynamic Impact Factor Assessment of Railway Bridges through a Radar Interferometer. *Remote Sens.* **2019**, *11*, 2207. [CrossRef]
45. Gentile, C.; Bernardini, G. Radar-Based Measurement of Deflections on Bridges and Large Structures. *Eur. J. Environ. Civ. Eng.* **2010**, *14*, 495–516. [CrossRef]
46. Gagliardi, V.; Tosti, F.; Bianchini Ciampoli, L.; Battagliere, M.L.; D'Amato, L.; Alani, A.M.; Benedetto, A. Satellite Remote Sensing and Non-Destructive Testing Methods for Transport Infrastructure Monitoring: Advances, Challenges and Perspectives. *Remote Sens.* **2023**, *15*, 418. [CrossRef]
47. Lasri, O.; Giordano, P.F.; Limongelli, M.P.; Previtali, M. Remote Monitoring of a Concrete Bridge Using PSInSAR. *ce/papers* **2023**, *6*, 893–899. [CrossRef]
48. Tonelli, D.; Valentini, A.; Rocca, A.; Zorzi, S.; Lotti, A.; Zonta, D. Uncertainty Quantification of Satellite InSAR-monitoring of Bridges: A Case Study. *ce/papers* **2023**, *6*, 900–906. [CrossRef]
49. Milillo, P.; Giardina, G.; Perissin, D.; Milillo, G.; Coletta, A.; Terranova, C. Pre-Collapse Space Geodetic Observations of Critical Infrastructure: The Morandi Bridge, Genoa, Italy. *Remote Sens.* **2019**, *11*, 1403. [CrossRef]
50. Lanari, R.; Reale, D.; Bonano, M.; Verde, S.; Muhammad, Y.; Fornaro, G.; Casu, F.; Manunta, M. Comment on "Pre-Collapse Space Geodetic Observations of Critical Infrastructure: The Morandi Bridge, Genoa, Italy" by Milillo et al. (2019). *Remote Sens.* **2020**, *12*, 4011. [CrossRef]
51. Selvakumaran, S.; Rossi, C.; Marinoni, A.; Webb, G.; Bennetts, J.; Barton, E.; Plank, S.; Middleton, C. Combined InSAR and Terrestrial Structural Monitoring of Bridges. *IEEE Trans. Geosci. Remote Sens.* **2020**, *58*, 7141–7153. [CrossRef]
52. D'Amico, F.; Gagliardi, V.; Bianchini Ciampoli, L.; Tosti, F. Integration of InSAR and GPR Techniques for Monitoring Transition Areas in Railway Bridges. *NDT E Int.* **2020**, *115*, 102291. [CrossRef]
53. Ponzo, F.C.; Iacovino, C.; Ditommaso, R.; Bonano, M.; Lanari, R.; Soldovieri, F.; Cuomo, V.; Bozzano, F.; Ciampi, P.; Rompato, M. Transport Infrastructure SHM Using Integrated SAR Data and On-Site Vibrational Acquisitions: "Ponte Della Musica–Armando Trovajoli" Case Study. *Appl. Sci.* **2021**, *11*, 6504. [CrossRef]
54. Gagliardi, V.; Tosti, F.; Bianchini Ciampoli, L.; D'Amico, F.; Alani, A.M.; Battagliere, M.L.; Benedetto, A. Monitoring of Bridges by MT-InSAR and Unsupervised Machine Learning Clustering Techniques. In Proceedings of the Earth Resources and Environmental Remote Sensing/GIS Applications XII, Online, 13–18 September 2021.
55. Cusson, D.; Trischuk, K.; Hébert, D.; Hewus, G.; Gara, M.; Ghuman, P. Satellite-Based InSAR Monitoring of Highway Bridges: Validation Case Study on the North Channel Bridge in Ontario, Canada. *Transp. Res. Record* **2018**, *2672*, 76–86. [CrossRef]
56. Farneti, E.; Cavalagli, N.; Costantini, M.; Trillo, F.; Minati, F.; Venanzi, I.; Ubertini, F. A Method for Structural Monitoring of Multispan Bridges Using Satellite InSAR Data with Uncertainty Quantification and Its Pre-Collapse Application to the Albiano-Magra Bridge in Italy. *Struct. Health Monit.* **2022**, *22*, 353–371. [CrossRef]
57. Qin, X.; Ding, X.; Liao, M.; Zhang, L.; Wang, C. A Bridge-Tailored Multi-Temporal DInSAR Approach for Remote Exploration of Deformation Characteristics and Mechanisms of Complexly Structured Bridges. *ISPRS J. Photogramm. Remote Sens.* **2019**, *156*, 27–50. [CrossRef]
58. Xiong, S.; Wang, C.; Qin, X.; Zhang, B.; Li, Q. Time-Series Analysis on Persistent Scatter-Interferometric Synthetic Aperture Radar (PS-InSAR) Derived Displacements of the Hong Kong–Zhuhai–Macao Bridge (HZMB) from Sentinel-1A Observations. *Remote Sens.* **2021**, *13*, 546. [CrossRef]
59. Tonelli, D.; Caspani, V.F.; Valentini, A.; Rocca, A.; Torboli, R.; Vitti, A.; Perissin, D.; Zonta, D. Interpretation of Bridge Health Monitoring Data from Satellite InSAR Technology. *Remote Sens.* **2023**, *15*, 5242. [CrossRef]
60. Cusson, D.; Rossi, C.; Ozkan, I.F. Early Warning System for the Detection of Unexpected Bridge Displacements from Radar Satellite Data. *J. Civ. Struct. Health Monit.* **2020**, *11*, 189–204. [CrossRef]
61. Schlögl, M.; Widhalm, B.; Avian, M. Comprehensive Time-Series Analysis of Bridge Deformation Using Differential Satellite Radar Interferometry Based on Sentinel-1. *ISPRS J. Photogramm. Remote Sens.* **2021**, *172*, 132–146. [CrossRef]
62. Hu, J.; Guo, J.; Xu, Y.; Zhou, L.; Zhang, S.; Fan, K. Differential Ground-Based Radar Interferometry for Slope and Civil Structures Monitoring: Two Case Studies of Landslide and Bridge. *Remote Sens.* **2019**, *11*, 2887. [CrossRef]

63. Huang, Q.; Wang, Y.; Luzi, G.; Crosetto, M.; Monserrat, O.; Jiang, J.; Zhao, H.; Ding, Y. Ground-Based Radar Interferometry for Monitoring the Dynamic Performance of a Multitrack Steel Truss High-Speed Railway Bridge. *Remote Sens.* **2020**, *12*, 2594. [CrossRef]
64. Miccinesi, L.; Beni, A.; Pieraccini, M. Multi-Monostatic Interferometric Radar for Bridge Monitoring. *Electronics* **2021**, *10*, 247. [CrossRef]
65. Xing, C.; Wang, P.; Dong, W. Research on the Bridge Monitoring Method of Ground-Based Radar. *Arab. J. Geosci.* **2020**, *13*, 1267. [CrossRef]
66. Olaszek, P.; Świercz, A.; Boscagli, F. The Integration of Two Interferometric Radars for Measuring Dynamic Displacement of Bridges. *Remote Sens.* **2021**, *13*, 3668. [CrossRef]
67. Talich, M.; Havrlant, J.; Soukup, L.; Plachý, T.; Polák, M.; Antoš, F.; Ryjáček, P.; Stančík, V. Accuracy Analysis and Appropriate Strategy for Determining Dynamic and Quasi-Static Bridge Structural Response Using Simultaneous Measurements with Two Real Aperture Ground-Based Radars. *Remote Sens.* **2023**, *15*, 837. [CrossRef]
68. Topczewski, Ł.; Cieśla, J.; Mikołajewski, P.; Adamski, P.; Markowski, Z. Monitoring of Scour Around Bridge Piers and Abutments. *Transp. Res. Procedia* **2016**, *14*, 3963–3971. [CrossRef]
69. Zheng, S.; Xu, Y.J.; Cheng, H.; Wang, B.; Lu, X. Assessment of Bridge Scour in the Lower, Middle, and Upper Yangtze River Estuary with Riverbed Sonar Profiling Techniques. *Environ. Monit. Assess.* **2017**, *190*, 15. [CrossRef] [PubMed]
70. Hou, S.; Jiao, D.; Dong, B.; Wang, H.; Wu, G. Underwater Inspection of Bridge Substructures Using Sonar and Deep Convolutional Network. *Adv. Eng. Inform.* **2022**, *52*, 101545. [CrossRef]
71. Hiasa, S.; Birgul, R.; Matsumoto, M.; Necati Catbas, F. Experimental and Numerical Studies for Suitable Infrared Thermography Implementation on Concrete Bridge Decks. *Measurement* **2018**, *121*, 144–159. [CrossRef]
72. Hiasa, S.; Necati Catbas, F.; Matsumoto, M.; Mitani, K. Considerations and Issues in the Utilization of Infrared Thermography for Concrete Bridge Inspection at Normal Driving Speeds. *J. Bridge Eng.* **2017**, *22*, 04017101. [CrossRef]
73. Pazhoohesh, M.; Zhang, C.; Hammad, A.; Taromi, Z.; Razmjoo, A. Infrared Thermography for a Quick Construction Progress Monitoring Approach in Concrete Structures. *Archit. Struct. Constr.* **2021**, *1*, 91–106. [CrossRef]
74. Ali, R.; Cha, Y.-J. Subsurface Damage Detection of a Steel Bridge Using Deep Learning and Uncooled Micro-Bolometer. *Constr. Build. Mater.* **2019**, *226*, 376–387. [CrossRef]
75. Karlsson, J. Corrosion Mechanisms under Organic Coatings—A Study in Relation to Next Generation's Pretreatments. Master's Thesis, Chalmers University of Technology: Gothenburg, Sweden, 2011.
76. Matsumoto, M.; Mitani, K.; Catbas, N.F.; Hiasa, S. Non-Destructive Structural Assessment Method Using Imaging Technology and Infrared Thermography. In *Life-Cycle of Structural Systems: Design, Assessment, Maintenance and Management*; CRC Press: Boca Raton, FL, USA, 2014.
77. Watase, A.; Birgul, R.; Hiasa, S.; Matsumoto, M.; Mitani, K.; Catbas, F.N. Practical Identification of Favorable Time Windows for Infrared Thermography for Concrete Bridge Evaluation. *Constr. Build. Mater.* **2015**, *101*, 1016–1030. [CrossRef]
78. Omar, T.; Nehdi, M.L. Remote Sensing of Concrete Bridge Decks Using Unmanned Aerial Vehicle Infrared Thermography. *Autom. Constr.* **2017**, *83*, 360–371. [CrossRef]
79. Ellenberg, A.; Branco, L.; Krick, A.; Bartoli, I.; Kontsos, A. Use of Unmanned Aerial Vehicle for Quantitative Infrastructure Evaluation. *J. Infrastruct. Syst.* **2015**, *21*, 04014054. [CrossRef]
80. Jáuregui, D.V.; White, K.R.; Woodward, C.B.; Leitch, K.R. Static Measurement of Beam Deformations via Close-Range Photogrammetry. *Transp. Res. Record* **2002**, *1814*, 3–8. [CrossRef]
81. Jiang, R.; Jauregui, D.V. A Novel Network Control Method for Photogrammetric Bridge Measurement. *Exp. Tech.* **2007**, *31*, 48–53. [CrossRef]
82. Jiang, R.; Jauregui, D.V. Development of a Digital Close-Range Photogrammetric Bridge Deflection Measurement System. *Measurement* **2010**, *43*, 1431–1438. [CrossRef]
83. Riveiro, B.; Jauregui, D.V.; Arias, P.; Armesto, J.; Jiang, R. An Innovative Method for Remote Measurement of Minimum Vertical Underclearance in Routine Bridge Inspection. *Autom. Constr.* **2012**, *25*, 34–40. [CrossRef]
84. Lubowiecka, I.; Arias, P.; Riveiro, B.; Solla, M. Multidisciplinary Approach to the Assessment of Historic Structures Based on the Case of a Masonry Bridge in Galicia (Spain). *Comput. Struct.* **2011**, *89*, 1615–1627. [CrossRef]
85. Carr, A.J.; Jáuregui, D.V.; Riveiro, B.; Arias, P.; Armesto, J. Structural Evaluation of Historic Masonry Arch Bridges Based on First Hinge Formation. *Constr. Build. Mater.* **2013**, *47*, 569–578. [CrossRef]
86. Stavroulaki, M.E.; Riveiro, B.; Drosopoulos, G.A.; Solla, M.; Koutsianitis, P.; Stavroulakis, G.E. Modelling and Strength Evaluation of Masonry Bridges Using Terrestrial Photogrammetry and Finite Elements. *Adv. Eng. Softw.* **2016**, *101*, 136–148. [CrossRef]
87. Dai, F.; Rashidi, A.; Brilakis, I.; Vela, P. Comparison of Image-Based and Time-of-Flight-Based Technologies for Three-Dimensional Reconstruction of Infrastructure. *J. Constr. Eng. Manag.* **2013**, *139*, 69–79. [CrossRef]
88. Popescu, C.; Täljsten, B.; Blanksvärd, T.; Elfgren, L. 3D Reconstruction of Existing Concrete Bridges Using Optical Methods. *Struct. Infrastruct. Eng.* **2019**, *15*, 912–924. [CrossRef]
89. Dong, C.-Z.; Catbas, F.N. A Review of Computer Vision–Based Structural Health Monitoring at Local and Global Levels. *Struct. Health Monit.* **2020**, *20*, 692–743. [CrossRef]

90. Narazaki, Y.; Hoskere, V.; Yoshida, K.; Spencer, B.F.; Fujino, Y. Synthetic Environments for Vision-Based Structural Condition Assessment of Japanese High-Speed Railway Viaducts. *Mech. Syst. Signal Process* **2021**, *160*, 107850. [CrossRef]
91. Narazaki, Y.; Hoskere, V.; Hoang, T.A.; Fujino, Y.; Sakurai, A.; Spencer, B.F. Vision-based Automated Bridge Component Recognition with High-level Scene Consistency. *Comput. Civ. Infrastruct. Eng.* **2019**, *35*, 465–482. [CrossRef]
92. Dorafshan, S.; Thomas, R.J.; Maguire, M. Comparison of Deep Convolutional Neural Networks and Edge Detectors for Image-Based Crack Detection in Concrete. *Constr. Build. Mater.* **2018**, *186*, 1031–1045. [CrossRef]
93. Bhattacharjee, S.; Deb, D. Automatic Detection and Classification of Damage Zone(s) for Incorporating in Digital Image Correlation Technique. *Opt. Lasers Eng.* **2016**, *82*, 14–21. [CrossRef]
94. Chen, P.-H.; Yang, Y.-C.; Chang, L.-M. Illumination Adjustment for Bridge Coating Images Using BEMD-Morphology Approach (BMA). *Autom. Constr.* **2010**, *19*, 475–484. [CrossRef]
95. Abdel-Qader, I.; Abudayyeh, O.; Kelly, M.E. Analysis of Edge-Detection Techniques for Crack Identification in Bridges. *J. Comput. Civ. Eng.* **2003**, *17*, 255–263. [CrossRef]
96. Zhang, L.; Yang, F.; Zhang, Y.D.; Zhu, Y.J. Road Crack Detection Using Deep Convolutional Neural Network. In Proceedings of the International Conference on Image Processing, ICIP, Phoenix, AZ, USA, 25–28 September 2016.
97. Dung, C.V.; Anh, L.D. Autonomous Concrete Crack Detection Using Deep Fully Convolutional Neural Network. *Autom. Constr.* **2019**, *99*, 52–58. [CrossRef]
98. Catbas, F.N.; Zaurin, R.; Gul, M.; Gokce, H.B. Sensor Networks, Computer Imaging, and Unit Influence Lines for Structural Health Monitoring: Case Study for Bridge Load Rating. *J. Bridge Eng.* **2012**, *17*, 662–670. [CrossRef]
99. Lee, J.J.; Cho, S.; Shinozuka, M.; Yun, C.; Lee, C.-G.; Lee, W.-T. Evaluation of Bridge Load Carrying Capacity Based on Dynamic Displacement Measurement Using Real-Time Image Processing Techniques. *Steel Struct.* **2006**, *6*, 377–385.
100. Dong, C.Z. Investigation of Computer Vision Concepts and Methods for Structural Health Monitoring and Identification Applications. Ph.D. Thesis, University of Central Florida, Orlando, FL, USA, 2019.
101. Celik, O.; Dong, C.-Z.; Catbas, F.N. A Computer Vision Approach for the Load Time History Estimation of Lively Individuals and Crowds. *Comput. Struct.* **2018**, *200*, 32–52. [CrossRef]
102. Khuc, T.; Catbas, F.N. Structural Identification Using Computer Vision–Based Bridge Health Monitoring. *J. Struct. Eng.* **2018**, *144*, 04017202. [CrossRef]
103. Dong, C.; Bas, S.; Debees, M.; Alver, N.; Catbas, F.N. Bridge Load Testing for Identifying Live Load Distribution, Load Rating, Serviceability and Dynamic Response. *Front. Built Environ.* **2020**, *6*, 46. [CrossRef]
104. Dong, C.-Z.; Bas, S.; Catbas, F.N. A Portable Monitoring Approach Using Cameras and Computer Vision for Bridge Load Rating in Smart Cities. *J. Civ. Struct. Health Monit.* **2020**, *10*, 1001–1021. [CrossRef]
105. Micu, E.A.; OBrien, E.J.; Malekjafarian, A.; McKinstray, R.; Angus, E.; Lydon, M.; Catbas, F.N. Identifying Critical Clusters of Traffic-Loading Events in Recurrent Congested Conditions on a Long-Span Road Bridge. *Appl. Sci.* **2020**, *10*, 5423. [CrossRef]
106. Zhang, J.; Kong, X.; OBrien, E.J. Computer Vision-Based Weight Identification and Stability Evaluation of Exceptional Transport Vehicles. *Eng. Struct.* **2023**, *294*, 116773. [CrossRef]
107. Gao, K.; Zhang, H.; Wu, G. A Multispectral Vision-Based Machine Learning Framework for Non-Contact Vehicle Weigh-in-Motion. *Measurement* **2024**, *226*, 114162. [CrossRef]
108. He, W.; Liu, J.; Song, S.; Liu, P. A Non-Contact Vehicle Weighing Approach Based on Bridge Weigh-in-Motion Framework and Computer Vision Techniques. *Measurement* **2024**, *225*, 113994. [CrossRef]
109. Yang, X.; Wang, X.; Podolsky, J.; Huang, Y.; Lu, P. Addressing Wander Effect in Vehicle Weight Monitoring: An Advanced Hybrid Weigh-in-Motion System Integrating Computer Vision and in-Pavement Sensors. *Measurement* **2024**, *234*, 114870. [CrossRef]
110. Catbas, F.N.; Luleci, F.; Zakaria, M.; Bagci, U.; LaViola Jr, J.J.; Cruz-Neira, C.; Reiners, D. Extended Reality (XR) for Condition Assessment of Civil Engineering Structures: A Literature Review. *Sensors* **2022**, *22*, 9560. [CrossRef]
111. Luleci, F.; Catbas, F.N. A Brief Introductory Review to Deep Generative Models for Civil Structural Health Monitoring. *AI Civ. Eng.* **2023**, *2*, 9. [CrossRef]
112. Karaaslan, E.; Bagci, U.; Catbas, F.N. Artificial Intelligence Assisted Infrastructure Assessment Using Mixed Reality Systems. *Transp. Res. Record* **2019**, *2673*, 413–424. [CrossRef]
113. Murray, C.; Hoag, A.; Hoult, N.A.; Take, W.A. Field Monitoring of a Bridge Using Digital Image Correlation. *Proc. Inst. Civ. Eng.-Bridge Eng.* **2015**, *168*, 3–12. [CrossRef]
114. Alipour, M.; Washlesky, S.J.; Harris, D.K. Field Deployment and Laboratory Evaluation of 2D Digital Image Correlation for Deflection Sensing in Complex Environments. *J. Bridge Eng.* **2019**, *24*, 04019010. [CrossRef]
115. Christensen, C.O.; Schmidt, J.W.; Halding, P.S.; Kapoor, M.; Goltermann, P. Digital Image Correlation for Evaluation of Cracks in Reinforced Concrete Bridge Slabs. *Infrastructures* **2021**, *6*, 99. [CrossRef]
116. Tian, Y.; Zhang, C.; Jiang, S.; Zhang, J.; Duan, W. Noncontact Cable Force Estimation with Unmanned Aerial Vehicle and Computer Vision. *Comput. Aided Civ. Inf. Eng.* **2020**, *36*, 73–88. [CrossRef]
117. Du, W.; Lei, D.; Bai, P.; Zhu, F.; Huang, Z. Dynamic Measurement of Stay-Cable Force Using Digital Image Techniques. *Measurement* **2020**, *151*, 107211. [CrossRef]
118. Dhanasekar, M.; Prasad, P.; Dorji, J.; Zahra, T. Serviceability Assessment of Masonry Arch Bridges Using Digital Image Correlation. *J. Bridge Eng.* **2019**, *24*, 04018120. [CrossRef]

119. Wang, Y.; Tumbeva, M.D.; Thrall, A.P.; Zoli, T.P. Pressure-activated Adhesive Tape Pattern for Monitoring the Structural Condition of Steel Bridges via Digital Image Correlation. *Struct. Control Health Monit.* **2019**, *26*, e2382. [CrossRef]
120. Halding, P.S.; Schmidt, J.W.; Jensen, T.W.; Henriksen, A.H. Structural Response of Full-Scale Concrete Bridges Subjected to High Load Magnitudes. In Proceedings of the Fourth Conference on Smart Monitoring, Assessment and Rehabilitation of Civil Structures, Zürich, Switzerland, 13–15 September 2017.
121. dos Santos, R.C.; Larocca, A.P.C.; de Araújo Neto, J.O.; Barbosa, A.C.B.; Oliveira, J.V.M. Detection of a Curved Bridge Deck Vibration Using Robotic Total Stations for Structural Health Monitoring. *J. Civ. Struct. Health Monit.* **2019**, *9*, 63–76. [CrossRef]
122. Manzini, N.; Orcesi, A.; Thom, C.; Brossault, M.-A.; Botton, S.; Ortiz, M.; Dumoulin, J. Performance Analysis of Low-Cost GNSS Stations for Structural Health Monitoring of Civil Engineering Structures. *Struct. Infrastruct. Eng.* **2020**, *18*, 595–611. [CrossRef]
123. Kaloop, M.R.; Li, H. Sensitivity and Analysis GPS Signals Based Bridge Damage Using GPS Observations and Wavelet Transform. *Measurement* **2011**, *44*, 927–937. [CrossRef]
124. Yi, T.-H.; Li, H.-N.; Gu, M. Experimental Assessment of High-Rate GPS Receivers for Deformation Monitoring of Bridge. *Measurement* **2013**, *46*, 420–432. [CrossRef]
125. Wang, J.; Meng, X.; Qin, C.; Yi, J. Vibration Frequencies Extraction of the Forth Road Bridge Using High Sampling GPS Data. *Shock. Vib.* **2016**, *2016*, 9807861. [CrossRef]
126. Ogundipe, O.; Roberts, G.W.; Brown, C.J. GPS Monitoring of a Steel Box Girder Viaduct. *Struct. Infrastruct. Eng.* **2012**, *10*, 25–40. [CrossRef]
127. Meng, X.; Nguyen, D.T.; Xie, Y.; Owen, J.S.; Psimoulis, P.; Ince, S.; Chen, Q.; Ye, J.; Bhatia, P. Design and Implementation of a New System for Large Bridge Monitoring-GeoSHM. *Sensors* **2018**, *18*, 775. [CrossRef] [PubMed]
128. Stiros, S.C. GNSS (GPS) Monitoring of Dynamic Deflections of Bridges: Structural Constraints and Metrological Limitations. *Infrastructures* **2021**, *6*, 23. [CrossRef]
129. Artese, S.; Zinno, R. TLS for Dynamic Measurement of the Elastic Line of Bridges. *Appl. Sci.* **2020**, *10*, 1182. [CrossRef]
130. Gucunski, N.; Boone, S.D.; Zobel, R.; Ghasemi, H.; Parvardeh, H.; Kee, S.-H. Nondestructive Evaluation Inspection of the Arlington Memorial Bridge Using a Robotic Assisted Bridge Inspection Tool (RABIT). In Proceedings of the Nondestructive Characterization for Composite Materials, Aerospace Engineering, Civil Infrastructure, and Homeland Security 2014, San Diego, CA, USA, 9–13 March 2014; Volume 9063.
131. La, H.M.; Gucunski, N.; Dana, K.; Kee, S. Development of an Autonomous Bridge Deck Inspection Robotic System. *J. Field Robot.* **2017**, *34*, 1489–1504. [CrossRef]
132. Phillips, S.; Narasimhan, S. Automating Data Collection for Robotic Bridge Inspections. *J. Bridge Eng.* **2019**, *24*, 04019075. [CrossRef]
133. McLaughlin, E.; Charron, N.; Narasimhan, S. Automated Defect Quantification in Concrete Bridges Using Robotics and Deep Learning. *J. Comput. Civ. Eng.* **2020**, *34*, 04020029. [CrossRef]
134. Seo, J.; Duque, L.; Wacker, J. Drone-Enabled Bridge Inspection Methodology and Application. *Autom. Constr.* **2018**, *94*, 112–126. [CrossRef]
135. Gordan, M.; Ismail, Z.; Ghaedi, K.; Ibrahim, Z.; Hashim, H.; Ghayeb, H.H.; Talebkhah, M. A Brief Overview and Future Perspective of Unmanned Aerial Systems for In-Service Structural Health Monitoring. *Eng. Adv.* **2021**, *1*, 9–15. [CrossRef]
136. Poorghasem, S.; Bao, Y. Review of Robot-Based Automated Measurement of Vibration for Civil Engineering Structures. *Measurement* **2023**, *207*, 112382. [CrossRef]
137. Duque, L.; Seo, J.; Wacker, J. Synthesis of Unmanned Aerial Vehicle Applications for Infrastructures. *J. Perform. Constr. Facil.* **2018**, *32*, 04018046. [CrossRef]
138. Rakha, T.; Gorodetsky, A. Review of Unmanned Aerial System (UAS) Applications in the Built Environment: Towards Automated Building Inspection Procedures Using Drones. *Autom. Constr.* **2018**, *93*, 252–264. [CrossRef]
139. Congress, S.S.C.; Escamilla, J.; Chimauriya, H.; Puppala, A.J. Eye in the Sky: 360° Inspection of Bridge Infrastructure Using Uncrewed Aerial Vehicles (UAVs). *Transp. Res. Record* **2023**, *2678*, 482–504. [CrossRef]
140. Wells, J.; Lovelace, B. *Unmanned Aircraft System Bridge Inspection Demonstration Project Phase II*; Minnesota. Department of Transportation, Research Services & Library: Saint Paul, MN, USA, 2017.
141. Gillins, D.; Parrish, C.; Gillins, M.; Simpson, C. *Eyes in the Sky: Bridge Inspections with Unmanned Aerial Vehicles*; SPR 787; The National Academies of Sciences, Engineering, and Medicine: Washington, DC, USA, 2018.
142. Ciampa, E.; De Vito, L.; Rosaria Pecce, M. Practical Issues on the Use of Drones for Construction Inspections. *J. Phys. Conf. Ser.* **2019**, *1249*, 012016. [CrossRef]
143. Ellenberg, A.; Kontsos, A.; Moon, F.; Bartoli, I. Bridge Related Damage Quantification Using Unmanned Aerial Vehicle Imagery. *Struct. Control Health Monit.* **2016**, *23*, 1168–1179. [CrossRef]
144. Hallermann, N.; Morgenthal, G.; Rodehorst, V. Unmanned Aerial Systems (UAS)—Case Studies of Vision Based Monitoring of Ageing Structures. In Proceedings of the International Symposium Non-Destructive Testing in Civil Engineering (NDT-CE), Berlin, Germany, 15–17 September 2015.
145. Hoskere, V.; Park, J.-W.; Yoon, H.; Spencer, B.F. Vision-Based Modal Survey of Civil Infrastructure Using Unmanned Aerial Vehicles. *J. Struct. Eng.* **2019**, *145*, 04019062. [CrossRef]

146. Stark, B.; Smith, B.; Chen, Y. Survey of Thermal Infrared Remote Sensing for Unmanned Aerial Systems. In Proceedings of the 2014 International Conference on Unmanned Aircraft Systems, ICUAS 2014—Conference Proceedings, Orlando, FL, USA, 27–30 May 2014.
147. Hallermann, N.; Morgenthal, G. Visual Inspection Strategies for Large Bridges Using Unmanned Aerial Vehicles (UAV). In *Bridge Maintenance, Safety, Management and Life Extension, Proceedings of the 7th International Conference of Bridge Maintenance, Safety and Management, IABMAS*; Shanghai, China, 7–11 July 2014, CRC Press: Boca Raton, FL, USA, 2014.
148. Perez Jimeno, S.; Capa Salinas, J.; Perez Caicedo, J.A.; Rojas Manzano, M.A. An Integrated Framework for Non-Destructive Evaluation of Bridges Using UAS: A Case Study. *J. Build. Pathol. Rehabil.* **2023**, *8*, 80. [CrossRef]
149. Potenza, F.; Rinaldi, C.; Ottaviano, E.; Gattulli, V. A Robotics and Computer-Aided Procedure for Defect Evaluation in Bridge Inspection. *J. Civ. Struct. Health Monit.* **2020**, *10*, 471–484. [CrossRef]
150. Kim, I.-H.; Jeon, H.; Baek, S.-C.; Hong, W.-H.; Jung, H.-J. Application of Crack Identification Techniques for an Aging Concrete Bridge Inspection Using an Unmanned Aerial Vehicle. *Sensors* **2018**, *18*, 1881. [CrossRef] [PubMed]
151. Kim, I.-H.; Yoon, S.; Lee, J.H.; Jung, S.; Cho, S.; Jung, H.-J. A Comparative Study of Bridge Inspection and Condition Assessment between Manpower and a UAS. *Drones* **2022**, *6*, 355. [CrossRef]
152. Li, H.-Y.; Huang, C.-Y.; Wang, C.-Y. Measurement of Cracks in Concrete Bridges by Using Unmanned Aerial Vehicles and Image Registration. *Drones* **2023**, *7*, 342. [CrossRef]
153. Beeram, S.K.; Kadarla, S.; Kalapatapu, P.; Pasupuleti, V.D.K. Structural Damage Identification from Video Footage Using Artificial Intelligence. In *European Workshop on Structural Health Monitoring. EWSHM 2022. Lecture Notes in Civil Engineering*; Springer: Cham, Switzerland, 2023; Volume 254.
154. Carroll, S.; Satme, J.; Alkharusi, S.; Vitzilaios, N.; Downey, A.; Rizos, D. Drone-Based Vibration Monitoring and Assessment of Structures. *Appl. Sci.* **2021**, *11*, 8560. [CrossRef]
155. Marchisotti, D.; Zappa, E. Feasibility of Drone-Based Modal Analysis Using ToF-Grayscale and Tracking Cameras. *IEEE Trans. Instrum. Meas.* **2023**, *72*, 5016210. [CrossRef]
156. Alani, A.M.; Tosti, F.; Ciampoli, L.B.; Gagliardi, V.; Benedetto, A. An Integrated Investigative Approach in Health Monitoring of Masonry Arch Bridges Using GPR and InSAR Technologies. *NDT E Int.* **2020**, *115*, 102288. [CrossRef]
157. Selvakumaran, S.; Plank, S.; Geiß, C.; Rossi, C.; Middleton, C. Remote Monitoring to Predict Bridge Scour Failure Using Interferometric Synthetic Aperture Radar (InSAR) Stacking Techniques. *Int. J. Appl. Earth Obs. Geoinf.* **2018**, *73*, 463–470. [CrossRef]
158. Ruthotto, L.; Haber, E. An Introduction to Deep Generative Modeling. *GAMM-Mitteilungen* **2021**, *44*, e202100008. [CrossRef]
159. Tomczak, J.M. *Deep Generative Modeling*; Springer International Publishing: Cham, Switzerland, 2022; ISBN 978-3-030-93157-5.
160. Bond-Taylor, S.; Leach, A.; Long, Y.; Willcocks, C.G. Deep Generative Modelling: A Comparative Review of VAEs, GANs, Normalizing Flows, Energy-Based and Autoregressive Models. *IEEE Trans. Pattern Anal. Mach. Intell.* **2022**, *44*, 7327–7347. [CrossRef]
161. Luleci, F.; Catbas, F.N.; Avci, O. A Literature Review: Generative Adversarial Networks for Civil Structural Health Monitoring. *Front. Built Environ.* **2022**, *8*, 1027379. [CrossRef]
162. Liu, J.; Wei, Y.; Bergés, M.; Bielak, J.; Garrett, J.H.; Noh, H.Y. Detecting Anomalies in Longitudinal Elevation of Track Geometry Using Train Dynamic Responses via a Variational Autoencoder. In *Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2019*; International Society for Optics and Photonics: Bellingham, WA, USA, 2019.
163. Entezami, A.; Sarmadi, H.; Salar, M.; De Michele, C.; Arslan, A.N. A Novel Data-Driven Method for Structural Health Monitoring under Ambient Vibration and High-Dimensional Features by Robust Multidimensional Scaling. *Struct. Health Monit.* **2021**, *20*, 2758–2777. [CrossRef]
164. Luleci, F.; Li, L.; Chi, J.; Reiners, D.; Cruz-Neira, C.; Catbas, F.N. Structural Health Monitoring of a Foot Bridge in Virtual Reality Environment. *Procedia Struct. Integr.* **2022**, *37*, 65–72. [CrossRef]
165. Hajdin, R.; Richter, R.; Rakic, L.; Diederich, H.; Hildebrand, J.; Schulz, S.; Döllner, J.; Bednorz, J. Digitalization of Bridge Inventory via Automated Analysis of Point Clouds for Generation of BIM Models. *ce/papers* **2023**, *6*, 1189–1197. [CrossRef]
166. Rodríguez, A.; Fuente, J.V.; Fabregad, R.; Álvarez, J.A.; Chacón, R.; Ramonell, C. Ground-Based Interferometer Radars for Load Tests of Long-Span Arch Bridges. Case Study: Almonte and El Tajo Viaducts, Extremadura, Spain. In *Bridge Safety, Maintenance, Management, Life-Cycle, Resilience and Sustainability, Proceedings of the 11th International Conference on Bridge Maintenance, Safety and Management, IABMAS 2022*; Barcelona, Spain, 11–15 July 2022, CRC Press: Boca Raton, FL, USA, 2023.
167. Arenas, J.J.; Merino, E.; García, P.; Capellán, G.; Martínez, J.; Beade, H.; Guil, Y. Analysis and Design of the Almonte Bridge. In Proceedings of the Engineering for Progress, Nature and People, Madrid, Spain, 3–5 September 2014.
168. Manterola, J.; Gil, M.Á.; Martínez, A.; Fuente, S.; Martín, B.; Blanco, L. Railway Arch Bridge over the Tajo River in the Alcántara Reservoir. In Proceedings of the Engineering for Progress, Nature and People, Madrid, Spain, 3–5 September 2014.
169. Capellán, G.; Merino, E.; Sacristán, M.; Martínez, J.; Guerra, S.; García, P. Almonte Viaduct: Design Principles and Structural Monitoring. In *Structural Integrity*; Springer International Publishing: Cham, Switzerland, 2020; Volume 11.
170. SAFEWAY. Available online: https://cordis.europa.eu/project/id/769255 (accessed on 21 August 2024).
171. Lamas, D.; Justo, A.; Soilán, M.; Riveiro, B. Automated Production of Synthetic Point Clouds of Truss Bridges for Semantic and Instance Segmentation Using Deep Learning Models. *Autom. Constr.* **2024**, *158*, 105176. [CrossRef]

172. Government of Portugal Monuments. Available online: http://www.monumentos.gov.pt/Site/APP_PagesUser/SIPA.aspx?id=6261 (accessed on 2 December 2021).
173. Luleci, F.; Chi, J.; Cruz-Neira, C.; Reiners, D.; Catbas, F.N. Fusing Infrastructure Health Monitoring Data in Point Cloud. *Autom. Constr.* **2024**, *165*, 105546. [CrossRef]
174. Luleci, F.; Catbas, F.N. Bringing Site to the Office: Decision-Making in Infrastructure Management through Virtual Reality. *Autom. Constr.* **2024**, *166*, 105675. [CrossRef]