D5.1 SHM DIGITAL TWIN REQUIREMENTS FOR RESIDENTIAL, INDUSTRIAL BUILDINGS AND BRIDGES

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ABSTRACT

This deliverable presents a report of the needs for structural control on buildings (initial imperfections, deflections at service, stability, rheology) and on bridges (vibrations, modal shapes, deflections, stresses) based on state-of-the-art image-based and sensor-based techniques. To this end, the deliverable identifies and describes strategies that encompass state-of-the-art instrumentation and control for infrastructures (SHM technologies).

KEYWORDS

Digital Twin, Building Information Modelling, Structural Health Monitoring, sensor, condition assessment, structural performance, damage detection

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DISCLAIMER

ACRONYMS & DEFINITIONS

BIM	Building Information Modelling
AR	Augmented Reality
VR	Virtual Reality
SHM	Structural Health Monitoring
CNN	Convolutional Neural Network
O&M	Operation and Maintenance
DT	Digital Twin
AI	Artificial Intelligence
CV-SHM-LL	Computer Vision-based Structural Health Monitoring Local Level
CV-SHM-GL	Computer Vision-based Structural Health Monitoring Global Level
IPA	Image processing and analysis
IFC	Industry Foundation Classes
BAS	Building Automation Systems
SAR	Synthetic Aperture Radar
DIAS	Data and Information Access Services
WSN	Wireless sensors network
CMMS	Computerized Maintenance Management Systems
HVAC	Heating, ventilation, and air conditioning
RFID	Radio Frequency Identification
IoT	Internet of Things
DOFS	Distributed optical fiber sensors
OMA	Operational Modal Analysis
CH	Cluster head
LVDT	Linear variable displacement transducer
FBG	Fiber Bragg Grating
CNN	Convolutional Neural Networks
PS	Phase Shift
TLS	Terrestrial Laser Scanner
GBInSAR	Ground-Based Interferometry SAR
TInSAR	Terrestrial Interferometry SAR
SAR	Synthetic Aperture Radar

GB RAR	Ground-Based Real Aperture Radar
JSON	JavaScript Object Notation

ASHVIN PROJECT

ASHVIN aims at enabling the European construction industry to significantly improve its productivity, while reducing cost and ensuring absolutely safe work conditions, by providing a proposal for a European wide digital twin standard, an open-source digital twin platform integrating IoT and image technologies, and a set of tools and demonstrated procedures to apply the platform and the standard proven to guarantee specified productivity, cost, and safety improvements. The envisioned platform will provide a digital representation of the construction product at hand and allow to collect real-time digital data before, during, and after production of the product to continuously monitor changes in the environment and within the production process. Based on the platform, ASHVIN will develop and demonstrate applications that use the digital twin data. These applications will allow it to fully leverage the potential of the IoT based digital twin platform to reach the expected impacts (better scheduling forecast by 20%; better allocation of resources and optimization of equipment usage; reduced number of accidents; reduction of construction projects). The ASHVIN solutions will overcome worker protection and privacy issues that come with the tracking of construction activities, provide means to fuse video data and sensor data, integrate geo-monitoring data, provide multi-physics simulation methods for digital representing the behaviour of a product (not only its shape), provide evidence based engineering methods to design for productivity and safety, provide 4D simulation and visualization methods of construction processes, and develop a lean planning process supported by real-time data. All innovations will be demonstrated on real-world construction projects across Europe. The ASHVIN consortium combines strong R&I players from 9 EU member states with strong expertise in construction and engineering management, digital twin technology, IoT, and data security / privacy.

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1 INTRODUCTION

Structural health monitoring (SHM) is required in the definition of Digital Twins (DT) regarding surveying the condition and thus managing decisions related to the built environment. The first leg of any system based on SHM is data collection. However, appropriately embedded data-collection within existing digital twin platforms is still in its infancy. It is necessary to implement compatible, state-of-the-art instrumentation for infrastructure control within centralized platforms.

On such a basis, sensor-, image- and remote sensor-based data need to be meaningfully collected and embedded within DT platforms according to specific asset characteristics. As a result, fully automated SHM systems can be established and then implemented in the construction projects. It is important to point out that different ways of collecting data provides generality, applicability and robustness to any SHM system. With that aim, this deliverable has been developed, providing the overview of state-of-the-art SHM technologies. The focus of the document is on the specific requirements one needs to account when it comes to data structure, data format and its corresponding match with numerical methods for further analysis. The description of these requirements together with an overview of state-of-the-art SHM systems is the content of the present deliverable.

1.1 STRUCTURAL HEALTH MONITORING (SHM): CONCEPT AND OBJECTIVES

A SHM system is defined as both “the observation” and “the analysis” of a built asset over time using periodically sampled response measurements to monitor changes to the material and geometric properties of engineering structures such as bridges and buildings.

The fundamental objective of SHM is to manage the risks and to take the appropriate decisions associated with an asset, including information for the assessment of the risks and for understanding how they might develop with time. In this sense, measuring and monitoring are just the initial parts of the full concept of SHM: the one related to data-collection. SHM comprises also the post-processing and analysis of the data to evaluate the performance of the asset as well as to provide the prognosis of the performance.

According to the main objective of SHM systems, three aspects are worth pointing out:

1) Design validation: to check whether the built asset behaves as planned at design stages. In bridges, this is usually carried out just after the completion of the structure via load tests.

2) Assessment of the structural performance. This is carried out along the service-life and operation of the asset. In this case, the development of SHM techniques is oriented to:
    a. The identification of sensitive characteristics (damage features) to small levels of damage
    b. the ability to distinguish the effects in the correct performance due to damage, from those due to changes in the ambient and operating

conditions (e.g. temperature, humidity, traffic in bridges, floor occupancy in buildings)

c. the development of statistical models that foster a better comprehension of damaged vs. undamaged configurations.
d. the development of methods concerning the definition of the optimal number and position of the sensors for accurately capturing the behaviour of the asset and its potential damage detection.

3) Improving asset management. SHM can provide more information about how an asset or its elements are behaving, leading to a better understanding and interpretation of the trends of how their physical state may change in time, so the optimum interventions and maintenance strategies can be developed to avoid future malfunctions and reduce costs due to the loss of structural performance (preventive maintenance).

In this deliverable, the term SHM is understood from a wide point of view covering both, the gathering of the structural response of the built asset (e.g. strains, strength, vibration), and the performance aspects of the asset (e.g. air quality, temperature comfort, energy consumption, structural safety)

1.2 DIGITAL TWIN: CONCEPT, OBJECTIVES ANDMETHODS

According to the National Infrastructure Commission in the UK, NIC (2017): “The digital twin is effectively a data representation of the infrastructure that takes real-time and other data into the management processes of that real-infrastructural component.” The Gemini Principles (CDBB 2018) define a digital twin as “a realistic digital representation of assets, processes or systems in the built or natural environment”. In this sense, a digital twin is not just a digital replica of a real/physical thing (for instance a digital photo or a BIM model), but “what distinguishes a digital twin from any other digital model or replica is its adequate real-time connection to its physical counterpart“. By “connection”, it is understood that there is an active relationship and association between the physical and digital parts. Therein lies the complexity of this concept. In addition, the links between DT and SHM systems appear since , measurement, analysis and decisions on the asset are expected both in the physical and digital parts.

A set of definitions for better understanding of DT in the built environment has been collected and identified recently (Dávila and Oyedele 2021). The Digital Twin paradigm originally defines an information construct that comprises the physical asset, its digital identical representation (a digital asset), and a data connection between them. Since physical-digital representations concerning the built environment are also developed, conceptual models including Cyber-Physical Systems and BIM are discussed by Dávila and Oyedele (2021). In any case, the further step in the existing frameworks (as BIM) to become a DT is the connection between the physical and the digital assets in nearly real time.

Digging further on these connections, it is recognised that linking physical and digital assets is possible through the deployment of a series of data-collection techniques in the physical asset that provide the feed to the digital twin in multiform ways. Again, similarities between SHM and DT arise. Together with verification and predictive numerical capabilities, the aim is to capture the present condition and predict the future performance of the physical asset, which will eventually provide enough data for an data-informed decision-making process. As sensing technologies (sensor-, image- or remote sensing based) become ubiquitous, smaller, more accurate, and more affordable, the ability to gather, process, and communicate the information increases. The human-centred interface between the two realms becomes an unprecedented way of intertwining both sensing and calculation capabilities.

In the case of a structure, the physical asset goes through several phases during its life-cycle. The design stage, the construction stage, and finally the operational phase, in which the maintenance and management becomes more relevant, represent three separate stages in all built assets. In the operational phase, or in the context of structural management, a DT may comprise several parts:

1) Structural inspection and data collection. Sensors, images and remote sensing techniques represent a variety of alternatives for data-collection.

2) IoT services. Adequate transmission, storage and data-structures represent a fundamental technology.

3) Data visualization in real time. A continuous understanding of the behaviour and characteristics of the asset. Visual monitoring and inspection in custom tailored human-computer interfaces.

4) Simulation and analysis. From reduced to full-order, models that allow a continuous verification of standard structural characteristics.

5) Data matching. Following standards from the industry, both simulated and collected data structures require interoperable formats.

6) Structural integrity quantification. Advanced automated data analysis, both data-driven or model-based, represent state-of-the art techniques that can be embedded in the virtual representation of the asset.

7) Performance prediction. Through complex analysis, advanced structural simulation models combined with deterioration models to predict future performance and anticipate damage location and extent.

In the case of operation and maintenance (O&M) management, research aiming at improving efficiency of the process based on some of the abovementioned parts is available. However, the majority of current works focus on specific implementations or disaggregated data resources. Some authors provide software architecture, some other improved real-time emergency response. A comprehensive overview and system architecture as required for a DT is available (Lu et al. 2020a, Dávila and Oyedele 2021)

Another example of framework for DT of building and civil infrastructures is proposed in Zandi et al. (2019). Challenges and opportunities related to the potential use of drones for inspection and monitoring, data-driven models for performance assessment and physics-based models for performance prediction, all together and inter-connected may derive on a living simulation platform (or DT) which updates itself after each inspection run. It is worth pointing out that these disaggregated elements coincide with the 7 parts of the DT SHM suggested system.

The virtualization of buildings and bridges in the last 15 years in the form of Building or Bridge Information Models is clearly identified as the starting point for the DT. The industry has erected a frame with semantically rich 3D reference standards and models that nowadays are enriched with time and sensor data from the DT perspective.

It is also worth pointing out that in many cases O&M of existing structures include assets that have never been digitised accordingly. Digital initial information for the asset is partial or even non-existent (lack of design drawings, construction quality control not available, …). Effort is thus required to establish the Digital Birth of the asset. Therefore, developing a digital asset from scratch for maintenance purposes suggest a “beyond BIM” representation in which connections between the physical and the digital realms are established whenever required.

In summary, DT are tools that can improve the understanding of performance of existing assets, to verify the as-built situation, run ‘what if’ simulations and scenarios, or provide a digital snapshot at any time. DT represent a comprehensive future regular SHM system. In the verge of data-driven, Artificial Intelligence (AI)-based decision-making techniques, constructing comprehensive DT will help taking data-based decisions for unexpected interventions and ultimately streamline costs throughout the asset’s operational life.

1.3 CONFLUENCE BETWEEN SHM AND DT

Attending to the previous definitions, objectives and contents of SHM and DT, it becomes evident that a close relationship and interaction between them is recommendable when facing the service life management of a built asset, building or bridge. The question here is as follows: is this interaction feasible and achievable?

Whether the answer is positive or not, the requirements and conditions for an efficient interaction deriving in the optimal data-supported decision-making process is analysed thoroughly the development of this deliverable.

1.4 0BJECTIVES OF THE DELIVERABLE

The main objective of this deliverable is to give an overview of the DT needs for structural health monitoring and control on buildings (initial imperfections, deflections at service, stability, rheology) and on bridges (vibrations, modal shapes, deflections, stresses) based on state-of-the-art image-based, remote sensing-based and sensor-based techniques. The needs are mainly related to the structural performance, although other parameters are also considered in buildings such as temperature, energy consumption and others. This is in accordance with the two approaches mainly performed in the construction sector as presented in figure 1.1 (excerpted from Dávila and Oyedele 2021).

One approach of this is the SHM, focusing on monitoring the behavior (globally) or identifying the structural faults and malfunctions (globally or locally) in infrastructure assets. The second approach is on the building services monitoring devoted to identifying faults in ventilation, heating, power, lighting, and water supply systems among others.

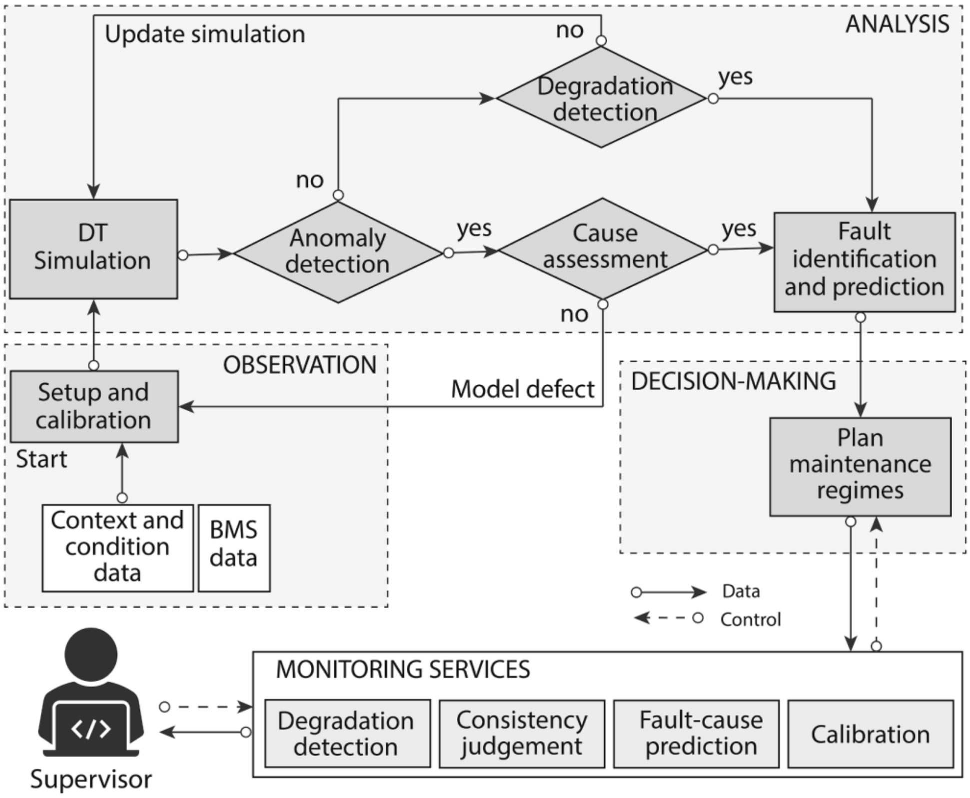


Figure 1.1: DT monitoring process model that can be used in the construction sector for SHM and building services monitoring (Davila and Oyedele 2021)

Therefore, state-of-the-art data-collection techniques (image-, remote-sensing and sensor-based) suitable for the development of DTs are presented in chapter 2. Based on the analysis of these techniques, requirements related to data format, data transmission, and data visualization are identified in chapter 3. In addition, the deliverable is also reporting on the state of the art in SHM systems and their requirements when facing a DT environment (chapter 4). Chapter 5 summarizes some of the implementations and SHM requirements identified in some of the ASHVIN demosites related to asset management and maintenance. The conclusions are collected in Chapter 6.

2 DATA COLLECTION

2.1 IMAGE-BASED METHODS

2.1.1 Introduction

One of the most straightforward techniques in the regular inspection process is the visual inspection, based on the recording of damages using a digital camera. This is usually used as a proof and a background for decisions made by the inspector during the condition assessment of the structure. Since it is very simple and nowadays very common to take several hundreds of pictures in a single inspection of an asset, one could claim that an enormous database on different damages exists. If these pictures are systematically organised, labelled and grouped according to different types and scope of damages, this would potentially present a very good starting point for the application of artificial intelligence approaches. Furthermore, in the last decade, numerous research and practice efforts have been made to implement UAV technology to monitor and inspect infrastructure (Chan et al. 2015, Seo et al., 2018, Znidaric et al. 2020, Bukhsh et al. 2022). By applying drones in visual inspections the amount of images is increasing even further. Therefore a drone-enabled inspection coupled with vision-based technology has the potential to serve as a more economical and safe alternative to conventional inspection and monitoring practices..

In this chapter main aspects of using digital images and videos for inspection, structural health monitoring and development of BIM models are explained.

2.1.2 IMAGES

Common basic processes in the application of digital images are image acquisition, image processing and image analysis.

- Acquisition is a process of recording an image, usually performed with high-resolution cameras (hand-held or with UAVs). In most cases the optimization and enhancement procedures related to the brightness, saturation, white balance, exposition, contrast etc. are performed automatically within camera.
- Digital image processing is the preparation of digital images for image analysis. It is worth remembering that each pixel of the image has associated values (measured in numbers). Some of these properties such as pixel colour may be altered during this processing.
- Image analysis is basically the numerical analysis of the processed values. Numerical information that characterises each pixel is evaluated. Manifold applications and selection of high-level understanding can be developed using those values.

These information are used then for inspection and/or monitoring of structures, for example for damage detection and classification, displacement measurement, load estimation, etc.

Main types of digital images are as follows:

1. Binary (1-Bit) images – each pixel is only black and white with only two values for each pixel which makes them easy for storage.
2. Greyscale (8-Bit) images – each pixel is a shade of grey from 0 (black) to 255 (white).
3. True colour or RGB (24-Bit) - each pixel has a particular colour; that colour being described by the amount of red, green and blue (RGB) in a 0-255 scale.

The resolution is the spatial scale of the image measured in pixels per unit area. For example, an image of 3300x2550 pixels with a resolution of 300 pixels per inch (ppi) would be a real world image size of 11" x 8.5". Resolution can be specified as (Solomon et al. 2011):

- Spatial resolution – number of recorded pixels by defining column (C) by row (R) dimensions and is referred to as the pixel or digital resolution of the image (CxR, 640x480, 800x600, 1024x768 etc.).
- Temporal resolution – used for videos and it presents number of images captured in a given time period. Unit frames per second (fps) is used to specify this type of resolution. The time resolution used for movies is usually 24 to 48 frames per second (fps), whereas high-speed cameras may resolve 50 to 300 fps, or even more.
- Bit resolution - number of possible intensity/colour values that a pixel may have (binary image has two colours (black or white), a grey-scale 256 different grey levels ranging from black to white while for a colour image it depends on the colour range.

There are several digital formats for storing raster images (set grid of dots/pixels), but the most common are JPEG, GIF, PNG, TIFF and RAW (Table 2.1).

- JPEG/JPG – is a format developed by Joint Photographic Experts Group (its name comes from the group). It is one of the most widely used formats. Due to compression, blurriness appears around edges of objects in the photo. Once compressed in JPEG format an image cannot be uncompressed (you cannot regain the original quality). JPEG is best used for online photos, print photos and quick preview image and not applicable for layered, editable images. It is often referred to as “lossy”, or in which information is lost.
- GIF – is a lossless raster format that stands for Graphics Interchange Format. GIF is typically used for animated graphics, email images and social media memes. GIFs files can be downsized by reducing the amount of colours and image information through exporting into a number of highly customizable settings. GIFs are not to be used when a photographic-quality image is needed, when printing is needed or when a layered, editable image is needed.
- PNG - Portable Network Graphics is a lossless raster format and is one of the most common image formats used online. This format has built-in transparency, but can also display higher colour depths then a GIF. Since PNGs are optimized for the screen they are not preferred for printing or working with photos.
- TIFF - Tagged Image File Format is a lossless raster with extremely high quality. The format is primarily used in photography and are typically very large (in terms of computer file size).
- RAW - an in-camera lossless format containing unprocessed data captured by a digital camera or scanner’s sensor. There are numerous raw formats, such

as CRW (Canon), NEF (Nikon), and DNG (Adobe). Typically, images are processed and then converted and compressed into another format (e.g. JPEG or TIFF).

Table 2.1 Common image formats and their associated properties (Solomon et al 2011.)

Acronym	Name	Properties
GIF	Graphics interchange format	Limited to only 256 colours (8 bit), lossless compression
JPEG	Joint Photographic Experts Group	In most common use today, lossy compression, lossless variants exist
BMP	Bit map picture	Basic image format, limited (generally) lossless compression, lossy variants exist
PNG	Portable network graphics	New lossless compression format, designed to replace GIF
TIF/TIFF	Tagged image (file) format	Highly flexible, detailed and adaptable format, compressed/uncompressed variants exist.
RAW	Unprocessed data	in-camera lossless format

Image processing and analysis is any form of signal processing for which the input is an image, such as a photograph or video frame. The output of image processing may be either an image or a set of characteristics or parameters related to an image. For example from geo-located images collected with the UAV and by using photogrammetric principles and algorithms, 3D point cloud model can be created, as explained in Section 2.3.

2.1.3 COMPUTER-VISION-BASED STRUCTURAL HEALTH MONITORING

Computer vision is an interdisciplinary scientific field that deals with how computers can gain high-level understanding from digital images or videos. Figure 2.1 shows an overview of use of computer vision based SHM at local and global level (Dong and Catbas 2020).

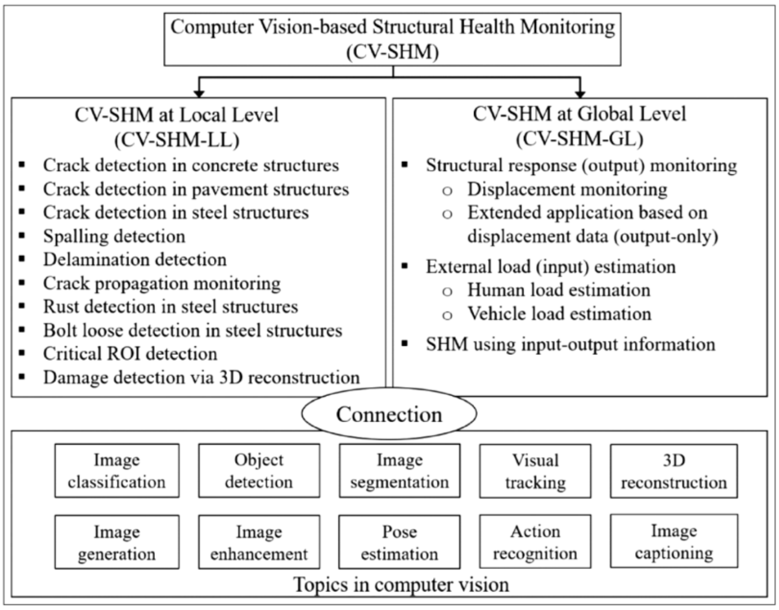


Figure 2.1: Overview of a computer vision-based SHM framework and general topics in computer vision (Dong and Catbas 2020)

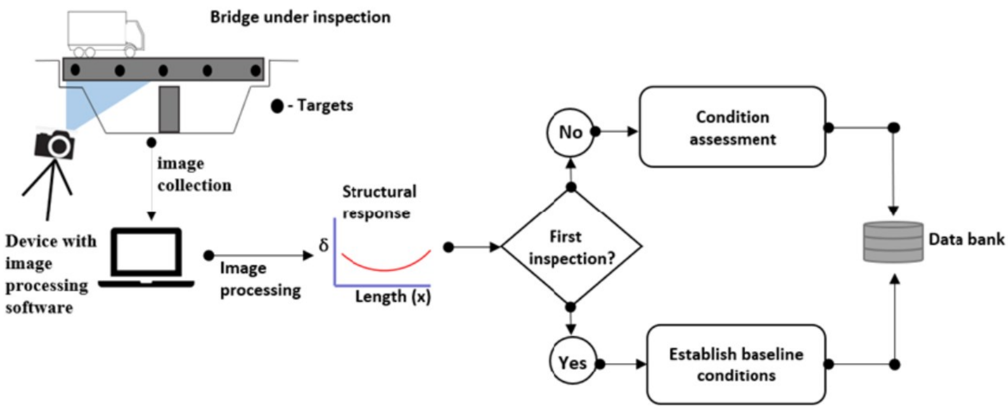


Figure 2.2: Vision-based SHM of bridges (Obiechefu and Kromanis, 2021)

The use of computer vision to measure structural displacement is discussed extensively in literature since displacement is a critical indicator of a structural performance (Ye et al. 2016, Feng et al. 2015). The main steps of the vision based SHM are presented in Figure 2.2.

Professional cameras with adequate lenses, camcorders, action cameras and smartphones are all suitable for accurate measurement collection (Kromanis et al. 2019). Structural response is extracted from image frames of a bridge under loading using either proprietary software (e.g., Video GaugeTM (Imetrum 2020)), open source software (e.g., QUBDisp (Lydon et al. 2019) and DeforMonit (Kromanis and Al-Habaibeh 2017)) or other image processing algorithms that detect and track targets in image frames. The cameras are placed in such a way that the anticipated structural responses under certain loading scenario can be measured. Generally there are two types of physical targets (or markers): artificial and natural targets. Natural targets are points on the structure which stand out from their surroundings and can easily be tracked. When no natural tracking points are present, one can place artificial targets on the structure. The advantage of using artificial targets is that the exact size and location can be determined by the user. The downside of artificial target is that the structure must be accessible to place the targets on the structure, e.g. bridge. By using natural targets this disadvantage can be overcome, since no access is needed. However, the target size needs to be known beforehand to be able to determine the actual displacement of the target.

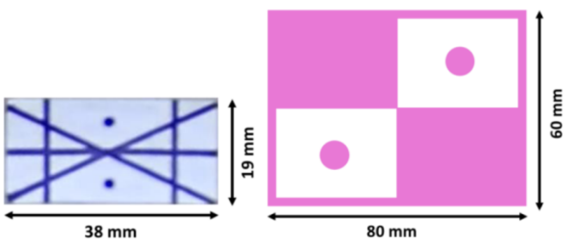


Figure 2.7: Examples of Artificial Markers

Physical markers used for target localization can be replaced with virtual markers (feature points) that are extracted from video frames by robust feature detection algorithms. These virtual markers represent textures or other unique surface characteristics of the structure. The virtual markers can be selected and plugged into the framework according to the best application for each scenario, which makes the whole framework more adaptive (Dong et al. 2019). Static and dynamic displacements can be obtained with high accuracy even by using smartphones and not expensive professional cameras (Kromanis et al. 2019). Also, the technique can be applied without the need to provide virtual markers what makes the methodology even more adaptive (Zhu et al. 2022).

Feature-based video image processing can be used for various measurements such as dynamic response of cables in cable-stayed bridges. Deterioration of cables could adversely affect the performance of the entire bridge structure. In vibration-based methods, the tensile forces in cables are estimated from the measurements of cable dynamic behaviour. Cable tension estimation using vision-based techniques has been investigated in structural health monitoring (SHM) of cable-supported bridges in numerous experimental studies (Chu et al. 2021).

A combination of cost effective cameras and available image processing algorithms for the derivation of structural response could become an affordable SHM system, which can complement regular visual inspections of structures.

2.1.4 Digital image processing and analysis for DT applications

Collected digital images are usually processed in the following steps and can provide different type of information about the analysed structure:

- Object recognition step – recognizing the object types of structure components (Barrile et al. 2019),
- Material recognition step – recognizing the material type of structure components (Lu 2020),
- Damage detection and classification – recognizing type and extent of damages – current condition assessment → towards digital twin (Bukhsh et al. 2021).

Image based 3D construction techniques for the retrieval of 3D structures information are broadly classified into two groups (Adhikari 2013):

- 3D point clouds captured directly by terrestrial laser scanners - heavy and not portable (Foltz 2000) as reported in section 2.3
- digital images or videos taken by digital cameras or camcorders - easy to use and portable, but the 3D information has to be estimated indirectly from multiple images or video frames shot under different directions

Image based results for structure components and defects are 2D projections and need to be translated into 3D models. This can be done from a single image taken from the correct corner, but high level information is rather collected through multiple images.

Figure 2.8 shows a BIM model of a bridge created based on photogrammetric data, technique that can be applied for developing 3D models of different types of assets.

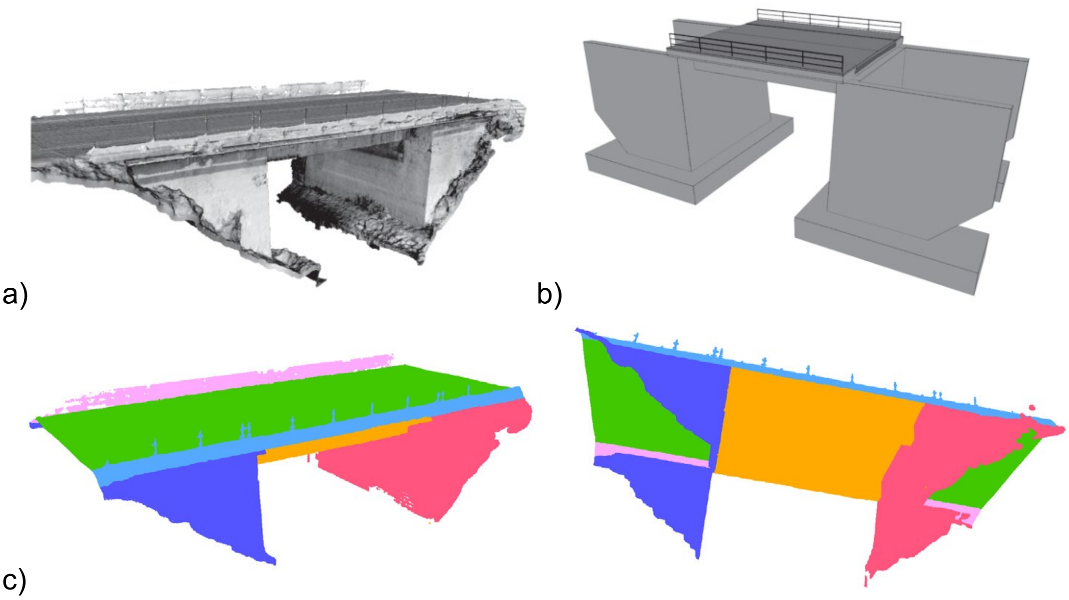


Figure 2.8: a) Photogrammetry-based 3D point cloud, b) As-designed BIM, and c) initially segmented as-is bridge point cloud. (Isailovic et al. 2020)

Methods for crack detection can be categorized into two main groups: patch-based crack detection and pixel-based crack detection. Crack detection methods can be used for detection of spalling and delamination in concrete structures, crack detection in pavement and steel structures, crack propagation monitoring etc.

In the patch-based method the basic procedure is to recognize whether cracks exist in a patch. The patch can be a sliding window crossing the whole images to do an exhaustive search with predefined stride or can be the sub-region which is segmented from the original image. Within the patch, pattern recognition, template matching, or classifier can be implemented to recognize whether there are cracks. In this process, machine learning, deep learning, or matching/recognition with manual features can be applied. In the pixel-based method, (see Figure 2.9), the whole image is processed directly, and cracks are segmented from the background. At the end, a detailed crack shape and distribution map is obtained (Dong and Catbas 2020).

In the case of image processing for crack detection in structural members, the main requirement is that clustering algorithms for pattern recognition (crack pattern and width) based on image processing should be fast enough for real-time crack detection. Different methods for crack detection using image processing techniques and Deep Learning Algorithms are summarized in Vijayan and Geethalakshmi (2018). From their analysis, it can be concluded that some methods are fast, but lack proper accuracy, whereas some other methods have high accuracy but restricted by complex computations, which leads to low speed. For real time processing, high speed and high accuracy are essential at the same time. They also conclude that each method is suitable for detection of some specific defects. Therefore, there is no general technique that has yet been proposed for detecting all different types of surface defects.

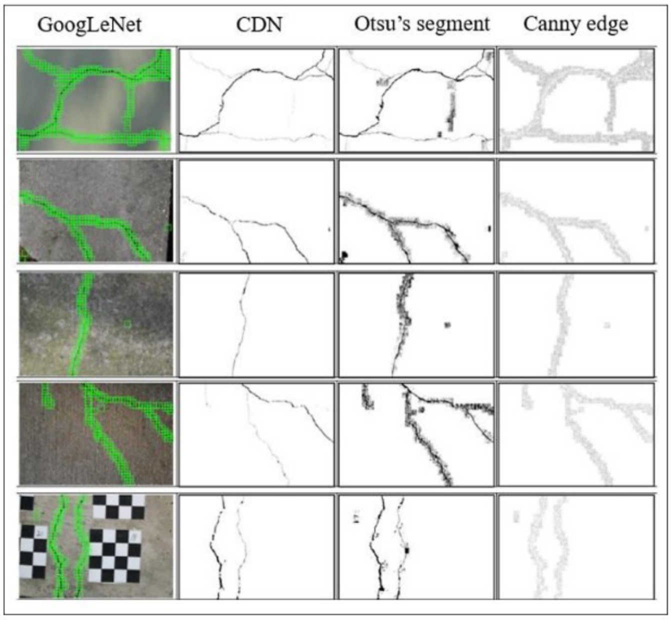


Figure 2.9: Patch-based (first column) and pixel-based crack detection (second to fourth column) (Ni et al. 2019)

In order to improve and automatize further visual inspections, ASHVIN aims to develop an automatic damage identification system using AI models, as it will be reported in D3.1. This will be then combined with risk based asset management models and used for the optimization of maintenance planning, which is part of tasks 5.2 and 5.3

2.2 SENSOR-BASED METHODS

2.2.1 INTRODUCTION

A digital twin normally for efficient monitoring and maintenance does not have to fully replicate the physical model in all aspects, but just the most important and characteristic parameters driving the in-service performance of the built asset, which can be defined as KPI (Key Performance Indicators, see deliverable 5.3 related to the subject). Not all the outputs of the physical model are of interest and therefore do not have to be replicated in the digital twin, but only the outputs that are relevant to check possible malfunctions of the system or that are necessary for the simulation/prediction of future performance. It is more likely that digital twins are not identical twins and the notion of an exact mirror is an idealization that will never be achieved. In this sense, the sensoring system should provide to the digital replica the necessary input data to accurately derive the KPI´s of interest. Therefore, the most adequate sensors will depend on the built asset under consideration and the required performance monitoring based on the evolution of the KPI´s of interest considered for the specific asset. Also, different phases can be considered in the life-cycle of the building: design, construction and operation. As different performances are expected in each phase, also different KPI´s will be considered in each of them (see deliverables 2.1, 4.1 and 5.3) and, therefore, different requirements for the sensors will be set depending on the design, construction and operation phases. **However, the following general requirements can be identified as general and of practical application for sensors in all phases of the building process in a DT environment:**

1. Connectivity to the digital twin (wireless, cable)
2. Proximity (measurement range)
3. Self-powered (energy requirements, harvesting)
4. Easy of deployment (bonded, embedded)
5. Distributed (nervous system)
6. Digitability: the ability to become digital.
7. Transmission speed: This will depend on the allowable lag between any input/output generated in the physical system and any measure of response to solve the problem to be provided by the DT.

A complete description of sensors for SHM in applications in the built environment is available in CIRIA (2020) and COST (2019). A review on the more advanced sensors for application in civil engineering and buildings is available in Das et al. (2018)

When looking into the operational and maintenance (O&M) phase of the building, in a review paper on the main sensor data used in bridge O&M around the world (Wu et al. 2022), it was identified that data collected by sensors for building management are divided into three main groups:

1. structural data: acceleration, and vibration (accelerometers, LVDT, GPS, GNSS) and strain and stress (strain gauges, vibrating wire, fibre-optic sensors (FBG and DOFS), pressure transducers and load cells) are the most common types because they are the basis for most structure analyses. Displacement and deflection mainly include vertical and horizontal displacement (LVDT, GPS) and rotation (inclinometers, tilt-meters, electro-level beams or gravity sensors)
2. environment data: temperature and wind data are widely collected due to their close influence with structures (thermocouples, anemometers, weather stations).
3. traffic data: the focus is on collecting traffic loads, especially the load of heavy trucks that can cause damages on the structure (FBG, weigh-in-motion systems)

Taheri (2019) presents a review of the recent achievements in the field of sensors developed for monitoring the health of concrete infrastructures. The focus is on sensors developed for monitoring parameters including concrete temperature, humidity, pH, corrosion rate, and stress/strain. In fact, with these 5 parameters, most of the damages present in concrete elements can be monitored. This is because corrosion of the reinforcement and cracking are the main damages in structural concrete that highly affect their safety, durability and sustainability. The sensors based on fiber optic, Bragg grating, piezoelectric, electrochemical, wireless, and self-sensing technologies have shown a high potential in detecting these damages (Figure 2.10). The main advantages and future challenges for further developing of these technologies is also presented in the paper by Taheri (2019).

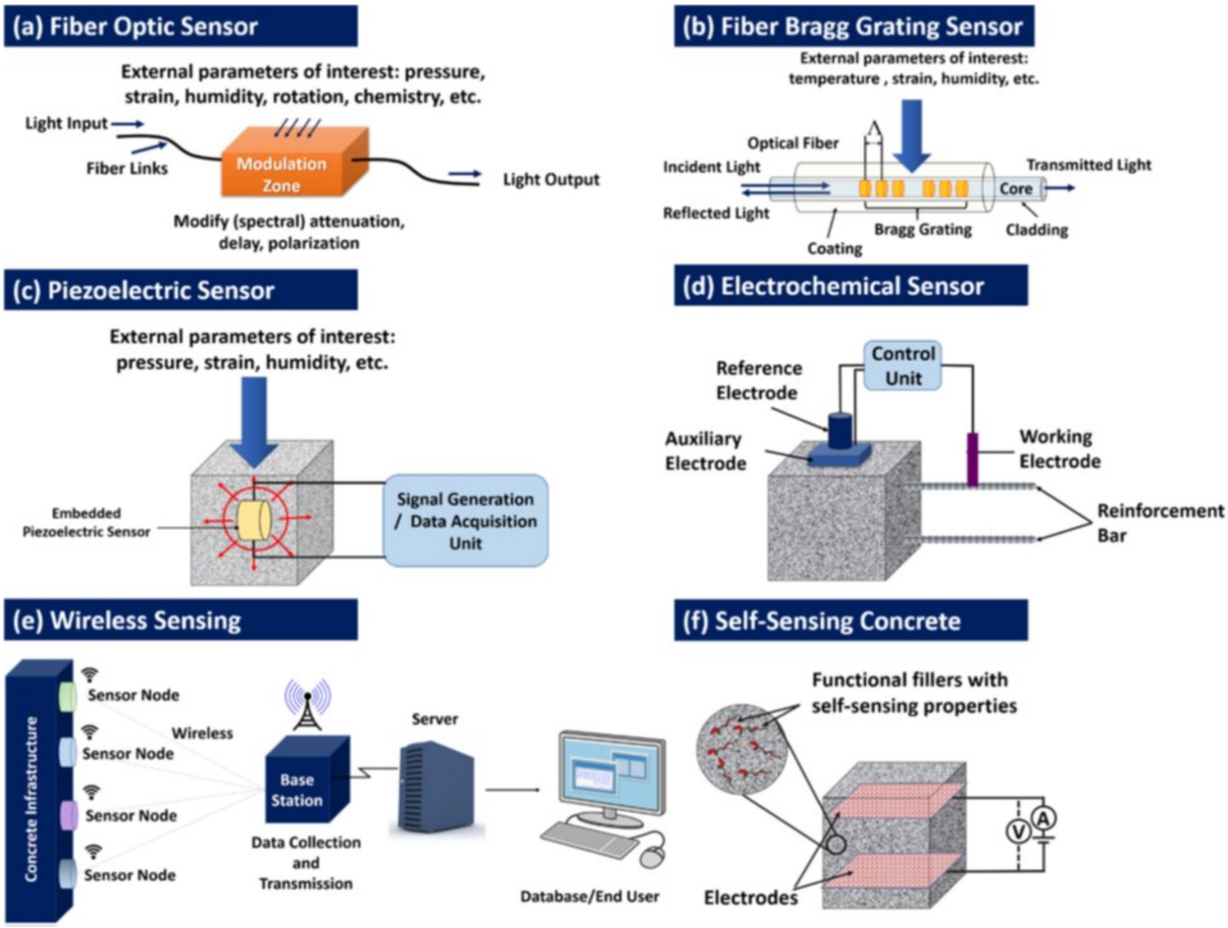


Figure 2.10. Advanced sensor technologies currently used in concrete SHM (Taheri 2019)

2.2.2 SENSORS FOR DT APPLICATIONS

All sensors have advantages and drawbacks when used in some specific monitoring scenarios. Therefore, a multi-sensor system can compensate for this issue. In this sense, it is of interest a data fusion process, combining inputs from various sensors.

From the high number of sensors available (CIRIA 2020, COST 2019), only those more suited for their use on a DT framework are presented in the following. The research into the development of new advanced sensors is oriented to simultaneously reduce the power consumption and weight of the system, to resolve deployment problems, and to improve operation facilities and the subsequent data analysis and post-processing. All these fields of research will derive, at the end, in better suited sensors to be used in a DT environment.

2.2.2.1 Piezolectric sensors

Piezoelectric materials are built from ceramic and polymers, and they present the direct and inverse piezoelectric effect. This is the reason these materials are often used to make vibration-based sensors and actuators and used as the basis for accelerometers and for acoustic emission sensors to detect corrosion and fatigue in concrete and metallic structures.

2.2.2.2 MEMS (Micro Electro-Mechanical Systems)

Micro-Electro-Mechanical Systems, or MEMS, is a technology that in its most general form can be defined as miniaturized mechanical and electro-mechanical elements that are made using the techniques of microfabrication. The critical physical dimensions of MEMS devices can vary from below one micron on the lower end of the dimensional spectrum, all the way to several millimeters.

MEMS can incorporate both micro-sensors and micro-actuators. An extremely large number of microsensors for almost every possible sensing modality including temperature, pressure, inertial forces, chemical species, magnetic fields, radiation, are becoming available. In particular, acceleration is easily monitored using MEMS. Based on the use of accelerometers, also tilt measurements can be carried out (Ha et al. 2013). More recently, the MEMS research and development community has demonstrated a number of microactuators such as: microvalves for control of gas and liquid flows; optical switches and mirrors to redirect or modulate light beams; independently controlled micromirror arrays for displays, microresonators for a number of different applications, micropumps to develop positive fluid pressures, microflaps to modulate airstreams on airfoils, as well as many others. With MEMS, it is now possible to create microsensors for the detection of mechanical quantities like pressure, vibration, acceleration, etc. that include signal conditioning and data samplers that can easily communicate with data acquisition and storage systems. In this scenario, for their cheap cost and their always increasing performances, MEMS based transducers are very interesting as they can significantly extend the range of applications of embedded sensors when compared to conventional ones.

An important advantage of MEMS is their ability to easily connect to a wireless sensor network (see chapter 4.1.1). MEMS consist of the integration of different types of sensors and are used to measure acceleration, angular velocity (gyroscopes), displacement, and deformation. Villacorta et al. (2021) presented the design, development and testing of a low-cost SHM system based on MEMS tri-axial accelerometers. The sensing element in MEMS accelerometers is comprised of a micro-machined proof mass that is suspended between two parallel plates. As the proof mass moves when acceleration is applied, one air gap decreases and the other gap increases creating a change in capacitance proportional to acceleration. In their work they compare the accuracy of MEMS accelerometers with traditional piezoelectric accelerometers showing the good performance of MEMS devices at a cost 10 times lower.

2.2.2.3 Fiber optics

Modern monitoring technologies aim at tackling the limitations of standard sensors, thus boosting the sensors' precision, automation, and data management speed. In particular, optical fiber sensors (OFS) are dielectric devices used to confine and guide light consisting of several layers: fiber core, cladding and coating (Figure 2.11) For protecting the fragile glass fiber against incidental mechanical damage and to enable appropriate manipulation a protective primary coating is applied directly in the production process (usually with an external diameter of 250 µm). Depending on the final application of the optical fiber, different numbers and types of additional protective jackets are used to ensure the mechanical and chemical resistance of the fiber when deployed in harsh environments.

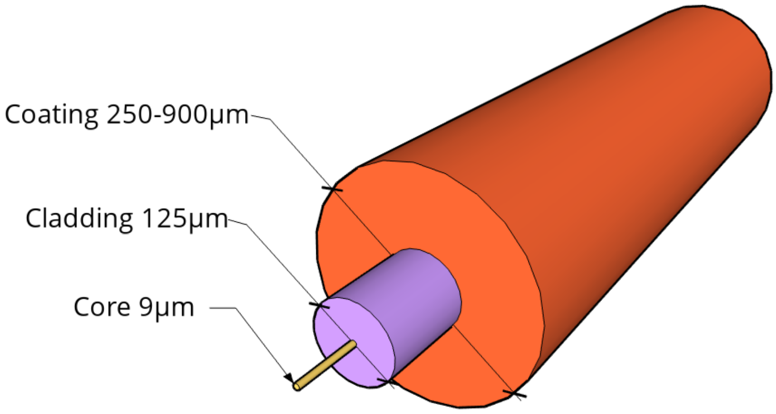


Figure 2.11: 3D illustration of a optical fiber cross-section

The majority of optical fibers used in sensing applications have silica (SiO2) glass cores and claddings. The refractive index of the cladding is lower than that of the core to satisfy the condition of Snell's law for total internal reflection and thus confine the propagation of the light along the fiber core only. The constituting material of the cladding, usually made of polymeric material or nylon, can vary in diametrical size, shape and manufacturing process.

The technology behind the OFS-powered strain sensing has recently upped its performance in terms of accuracy, spatial resolution, resistance and in number of possible applications, consequently increasing their potential use in several fields, particulalry in civil engineering (Barrias and Casas 2016, Bado and Casas 2021).

The increased popularity for SHM applications can be attributed to the following OFS features:

- Small diameter and minimal stiffness allow for very high degrees of deployment configuration complexity, no matter if these imply circumferential surfaces, sharp corners, surface irregularities and more. It is even possible to embed them inside structural elements with a minimal level of intrusiveness.
- Ease of deployment by simply applying an adhesive over it.
- Their monitoring length is very flexible and can vary from halves of millimeter to tens of kilometers
- Immunity to Electro-Magnetic Interference (EMI)
- They are designed with a long lifetime cycle in mind, as its main component, silica, is highly resistant to corrosion and can withstand high tensile loading
- Silica core OFS are highly resistant to temperature and can measure temperatures from -200°C to 800°C.

2.2.2.3.1 Discrete sensors

Standard FBG

Up to now, the great majority of photonic sensing technology employed in SHM is consists of discrete sensors such as Fiber Bragg Gratings (FBG). These are quasi-distributed optical fiber sensors in which a characteristic wavelength is used to simultaneously provide its address in the sensor network, and the measurement (temperature and strains).

It can be easily argued that the most crucial limitation of discrete sensors lies in their non-distributed nature. This shortcoming is quite critical in the context of SHM as it prevents the possibility of precisely pointing out the location where a potential damage first occurs and prevents the linking of local damage mechanisms to the global condition of the structure. This is also the problem of OFS of the discrete type. A first solution to this problem is the multiplexing, which consists of the application of several FBG within the same Optical fiber. This allows to monitor a profile consisting of several points of measurement. However, even with the multiplexing, the achieved spatial resolution is not high. Therefore, the final solution is using OFS measuring system in a distributed way as described later on.

FBG-based ultrasonic sensors

In normal operation, FBG can detect temperature and strain. However, they also can detect ultrasonic signals if the sensor head and the corresponding demodulation system are properly designed. A FBG is barely sensitive to the ultrasonic wave when the ultrasonic wavelength is smaller than the grating length. Thus, the FBG sensor should be sufficiently short to fully receive all frequency information in a Lamb wave. As a result, there is a conflict between the sensitivity and the bandwidth when a conventional FBG sensor is used for ultrasonic detection. To solve this issue and increase the sensitivity of the FBG to ultrasonic signals a special FBG was developed. A Phase-Shifted FBG (PSFBG), which is a special type of FBG, has unique characteristics in ultrasonic detection. Its manufacturing process is similar to that of normal FBG, except that a π phase-shift is inserted in the middle of the grating area. The spectrum of a PSFBG has the same grating length, grating period, and refractive index as the uniform FBG. However, the slope in the valley of the PSFBG spectrum is steep and the full width at half maximum (FWHM) of the valley is narrow. These characteristics are beneficial not only for static measurements but also for ultrasonic detection. First, the ultrasonic sensitivity can be better than that of a uniform FBG due to its steep slope at the central peak (or valley) of the spectrum. Furthermore, a PSFBG confines its light field to the phase-shifted area and its effective length could be very short, thereby allowing it to detect ultrasonic signals up to the megahertz range (Wu et al. 2018, Rosenthal et al. 2011)

2.2.2.3.2 Distributed sensors

Distributed Optical Fiber Sensors (DOFS) are also mainly used for strain and temperature measurements. Their fundamental capability is to measure mechanical and temperature-variation induced strains along a fiber's length by means of light back-scattering occurring whenever the photons of the emitted light interact with the physical medium through which it travels (the fiber's core itself).

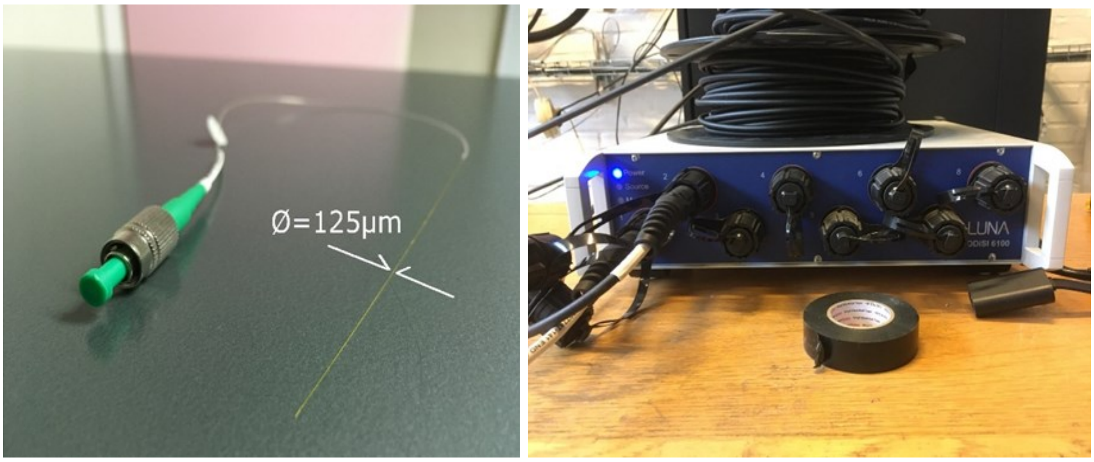
A comprehensive review of the use of DOFS in structures and the built environment is available in Barrias et al. (2016) comprising the applications until 2016 and further in Bado and Casas (2021), where the realizations in the period 2016 to 2021 are presented.

Different backscattering technologies are available for measurement of strain, temperature, and sound (through the so-called Distributed Acoustic Sensing (DAS) with a wide range of sensing ranges from some meters up to some kilometers and spatial resolution (Table 2.3).

Table 2.3: Performance differences between the various DOFS sensing techniques (Barrias et al. 2016)

Sensing Technology	Transducer type	Sensing range	Spatial Resolution	Main object of measurement
Raman OTDR	Distributed	1 km 37 km	1 cm 17 m	Temperature
Brillouin BOTDR	Distributed	20-50 km	≈1 m	Temperature and Strains
Brillouin BOTDA	Distributed	150-200 km	2 cm (2 km) 2m (150 km)	Temperature and Strains
Rayleigh OFDR/DAS	Distributed	50-70 m	≈1 mm	Temperature, Strains and Vibration
FBG (multiplexed)	Quasi-distributed	≈100 channels	2 mm (Bragg length)	Temperature and Strains and displacement

The lack of sufficient monitoring points along a fiber deployment (spatial resolution) is an issue entirely surpassed by DOFS (Figure 2.12a). As a matter of fact, the latest model of DOFS sampling Optical Backscatter Reflectometer (OBR) Interrogator machines (Figure 2.12b) can monitor strains with a spatial resolution of 0.63 mm with an accuracy of 1 microstrain. The sampling rate is relatively low, what makes them not well suited for high frequency measurements.



(a) **(b)**

*Figure 2.12: **(a)** DOFS fiber and **(b)** ODiSI-6000 model OBR interrogator manufactured by LUNA Technologies*

The distributed nature of such fibers enables the mapping of temperature, strain and vibration distributions in two or even three dimensions (achievable with a DOFS mesh deployment as presented in Rodríguez et al. (2019 a,b) and their identification at any point along a fiber, henceforth allowing capturing a clear picture of the global behavior of a structure rather than reporting the tensile state of a limited number of points.

Berrocal et al. (2021) investigates the suitability of DOFS for the assessment of performance requirements, namely, deflections and cracking (including crack width measurements), in RC structures. In addition, they devised a post-processing procedure to show that intuitive contour plots of the beam's crack pattern can be generated based on the strain measurements of DOFS deployed at different beam heights.

In **distributed acoustic sensing (DAS**) an optical fiber is transformed into an array of thousands of "virtual microphones." DAS technology is based on Rayleigh backscattering phenomenon occurring of DFOS. Using appropriate interrogation schemes and analyses, the dynamic functionality of DOFS can transform a conventional fiber into a kilometers-long array of "virtual sensors" (or "virtual microphones") that can detect and locate acoustical signals and vibrations along its entire length. Distributed acoustic sensing (DAS) is a technology that utilizes the phenomenon that the phase of the Rayleigh backscattered light in the optical fiber is highly sensitive to the external acoustic signals and mechanical vibrations. The external dynamic perturbations can be quantified and located as a function of distance along the whole optical fiber through appropriate interrogation schemes. Thanks to the continuous optimization of the performance, state-of-the-art DAS systems are capable of quantifying and locating perturbations with a distance resolution down to meter scale over a distance of tens of kilometers (Gabai and Eyal 2016). DAS transforms an optical fiber into a distributed array of acoustic sensors, which is an analog to the microphone array or antenna array, and the array signal processing (ASP) methods developed in these fields can be used for DAS.

Jiajing et al. (2019) establish a new method for a DAS system with the capability of two-dimensional (2D) and three-dimensional (3D) acoustic source localization. This facilitates new areas of applications such as location and identification for static, dynamic and multiple targets in air or water.

Phase-sensitive optical time-domain reflectometry (ϕ-OTDR) based on coherent detection is one of the most widely used schemes to achieve fiber distributed acoustic sensing. By using this technology, a linear response of the vibration intensity is realized with a long measurement range of about 30 km, 3-to-10-meter spatial resolution and a 3 kS/s sampling rate to the vibration signals (Yang et al. 2016). The accuracy is of the order of 0.1 microstrain

2.2.2.4 Electromagnetic sensors

Gkantou et al. (2019) showcased the possibility of applying novel microwave sensors for crack detection in reinforced concrete structures. The microwave measurements were analyzed and compared with those from crack width gauges. A strong linear relationship between crack propagation and electromagnetic signal across the full captured spectrum was found, demonstrating the technique's capability and its potential for further research, offering a reliable, low-cost option for SHM and DT capabilities.

2.2.2.5 Accelerometers

Accelerometer is a type of sensor widely used in the monitoring of the built environment (buildings, bridges, dams) under dynamic action. This is due to its easy deployment in existing structures. Different principles can be used to manufacture acceleration sensors. There are different accelerometer types based on piezoelectric materials, in MEMS and in fiber optics. The most widely used have traditionally been the piezoelectric crystal ones, which are highly accurate and sensitive. However, these accelerometers are expensive, potentially reducing their availability for tests with large set-ups. Besides, their high economic value also limits the possibility of using them just for a short test period, and they can rarely be used for continuous real-time measurements. In the last decade, new digital acceleration sensors based on the Micro Electro-Mechanical Systems (MEMS) technology were applied to structural health monitoring with promising results. These MEMS digital accelerometers provide similar measurement to traditional devices, but at a much lower price, reduced size, and good performance (Villacorta et al. 2021).

For the measurement of acceleration in built infrastructure, the minimum required sampling resolution is at least 16 bits with a sampling frequency of 100 Hz.

Innovative use of accelerometers in SHM that may have a relevant application in digital twinning of bridges is under investigation. Normally, sensors are attached to the surface or embedded into the structure and, therefore, placed on a fixed location. However, for bridges, the use of monitoring by sensors mounted on vehicles has been already researched and is likely to increase. These take measurements of deflection and/or acceleration of the vehicle as it passes over the bridges or pavements. Such acceleration records can give a more comprehensive view than from sensors set in a few fixed locations on the asset. In recent years, the possibility of monitoring bridges by indirectly sensing relevant parameters from traveling vehicles has emerged as an approach that would allow for the elimination of the costly installation of sensors and monitoring campaigns. This methodology, known as **drive-by monitoring** is very attractive because of the enhanced opportunities of application of dynamic tests as a tool for periodic inspections while significantly mitigating their impact on the traffic flow. The instrumented vehicle acts as a dynamic measurement device for monitoring and provides valuable information on the structural response of the bridge at a low-cost. Vibration data gathered by sensors mounted on cars might represent a valuable alternative to get the modal characteristics of bridges by standard fixed sensors. Moreover, these indirect methods have the potential of opening the way to new frontiers of dynamic identification, since they well fit the basic features of the crowd-sensing. Based on current trends in the field of automotive, more and more vehicles are indeed equipped with sensors, such as accelerometers, which could potentially yield huge amounts of vibration data. The studies developed so far confirmed that only at low vehicle speeds it is possible to achieve adequate frequency resolution for the estimation with sufficient accuracy of the first vibration frequency of a bridge (Siringoringo and Fujino 2012). To obtain longer vibration records and therefore increase the accuracy and resolution, a possibility is to obtain indirect measurements of the vibration response of the tested bridge by means of instrumented vehicles at rest on the bridge itself. These sensors-equipped vehicles at rest on the tested bridge might be the cars used by bridge inspectors for the periodic in-situ checks. This approach allows the collection of sufficiently long records while making the execution of OMA (operational modal analysis) tests faster by skipping the sensor installation phase. In addition, the mobility of the vehicle can be exploited to perform multiple tests on different bridges of the network in a relatively short time, thus reducing the costs associated to traffic control and limitation (Ercolessi et al. 2021). The vibration in the passing vehicle is monitored and therefore, the vehicle is used as a moving sensor that can gather data from a large number of bridges in a short period of time, overcoming the cumbersome operations of sensor deployment. The methodology requires the preliminary characterization of the dynamic properties of the vehicle (calibration) and sensors characterized by high dynamic range to resolve with adequate accuracy the dominant response of the instrumented vehicle as well as the (typically low amplitude) response of the bridge. The use of this technique for damage detection in bridges is further detailed in section 4.2.2.

Gkoumas et al. (2021) discusses the needs for using CCAM (cooperative, connected, and automated mobility) in the drive-by monitoring of transport infrastructure. CCAM should be considered for the future development of iSHM (indirect structural health monitoring) strategies. The study identifies that additional research is necessary for better identification of structural deficiencies through drive-by monitoring. This includes a better understanding of the influence of the road roughness profile, the bridge length and type, the interacting vehicle load and geometry, the vehicle speed, the interaction time between the vehicle and the bridge, the temperature, and other environmental effects

2.2.2.6 *Self-Sensing and smart materials*

A self-sensing material exhibits a measurable property change in response to external stimuli. These materials can intrinsically report on their health or condition in a spatially distributed way. They also need less hardware and equipment than the standard sensing technologies. In most cases, the response to external actions (load, deformation) is based on the piezoresistive effect. They present a change in electrical resistivity upon deformation or pressure (Tallman and Smyl 2020). Therefore, in theory, every point in the material becomes a sensor. However, it is not feasible to deploy electrodes to measure conductivity changes at every point on a structure. Some materials exhibit the piezoresistive effect by themselves, but others that do not exhibit piezo-resistivity can be converted into self-sensing materials by adding an additional constituent. In this case, electrical transport is a consequence of percolation. The composite conducts electricity when sufficiently many conductive fillers have been added to form an electrically connected network.

In the built environment, self-sensing concrete is a field of increasing research. In self-sensing concrete, a transducer is used to both actuate and sense simultaneously. Materials with intrinsic sensing properties, such as carbon nanofibers (CNF), carbon nanotube (CNT), semi-conductive or conductive nanoparticles are mixed into concrete, forming concrete-based piezoelectric composites. The concept of self-sensing concrete is based on piezo-resistivity principle and changes in the volume of electrical resistivity of electrically conductive concrete. Concrete is mixed with carbon fiber, which comprises as much as 0.2% to 0.5% of the volume. This can detect changes in stress or strain in concrete structures before they fail. It works by adding a small quantity of short carbon fiber to concrete with a conventional concrete mixer to modify the electrical resistance of the concrete in response to strain or stress. As a result, the contact between the fiber and cement matrix is impacted when the concrete is deformed or stressed, thereby affecting the volume electrical resistivity of the concrete. The strain is then determined by measuring the degree of electrical resistance.

At the present time, the methodologies of converting the profile of electrical resistivity into mechanical parameters (change in strain or stress) are still not completely developed and many challenges should be still solved to achieve a reliable inverse analysis tool. However, in the case of concrete, the presence of cracks breaks the conductivity of the network and therefore increases the resistivity of the concrete. Smart concrete is capable of sensing very small structural flaws and hence finds application in checking the internal condition of structures. In addition, smart concrete also helps to arrest the progress of cracks, reinforcing them to make them stronger. Further, it takes a lot of force for smart concrete to bend, and it can accept more energy before fracture. Smart concrete can also find application in building highways able to detect the position, weight, and speed of vehicles.

Castañeda et al. (2021) presents a multipurpose study that includes the characterization of cementitious composites with inclusions of CNTs (carbon nanotubes), different test procedures, and a proof-of-concept demonstration in a simply supported reinforced concrete beam of the suitability of these types of sensors for strain-based SHM. The novelty focuses on the effective integration of the self-sensing concrete sensors in a structural member and in using information from them for damage detection based on strain, demonstrating their suitability for future practical SHM applications.

Environmental conditions and chemicals also affect the accuracy of the output of self-sensing concrete (Alonso and Puentes 2020).

In the same category of self-sensing and smart materials are included the textile-reinforced concrete (TRC). In TRC, multi-axial textile fabrics are used in combination with high-strength fine grained concrete. Typically, a TRC substrate consists of a matrix with a maximum aggregate grain size between 1 and 2 mm and high-performance continuous multifilament made of carbon, or polymer. The main advantages of TRC are its high tensile strength and flexible ductile behavior, which enables relatively thin-structured concrete elements. Due to the fabrication process of the textile, made of rovings, which contain several hundred to several thousand individual filaments of roughly 5–25 µm in diameter, it is relatively easy to **embed distributed optical fibers** within the grid, thus performing a reinforcement grid into the concrete able to measure strain in several specified directions. Different techniques are available for the automatic incorporation of optical fibers into textile-based reinforcement structures (Alwis et al. 2021).

Krzywon et al. (2016) presents a self-monitoring strengthening system based on carbon fibers. The textile obtained by deploying the fibers in 2 directions is able not only to strengthen concrete structures when bonded externally to the surface, but also, to self-monitoring their strain. The carbon fibers play the role of not only tensile reinforcement but also strain sensor. However, the same authors have shown that the strain measurement with carbon fibers is very sensitive to temperature changes, and, therefore, applications of this method in practice require temperature compensation (Górski et al. 2018).

2.2.2.7 Corrosion sensors

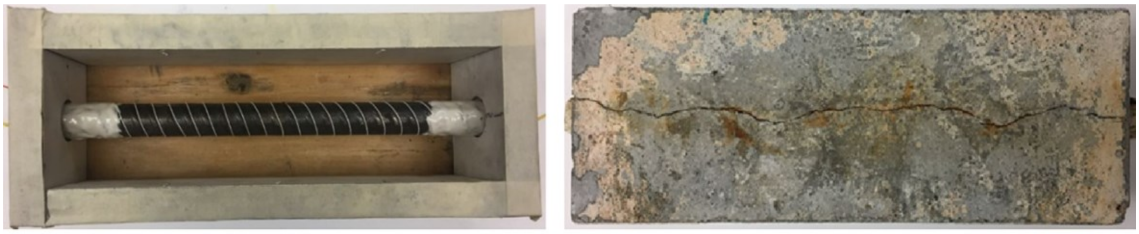
Corrosion of the embedded reinforcement is the most common deterioration in reinforced concrete structures and is also jointly with fatigue a main stressor in steel structures. For this reason, corrosion sensors deserve a top position in the ranking of most used sensors in the built environment. In a corroding concrete element, the corrosion rate can be determined directly or indirectly by monitoring factors such as concrete humidity, chloride content, pH value, concrete resistivity, or the depth of chloride ion penetration into the concrete. A complete description of sensors for the monitoring of these parameters related to corrosion in concrete structures can be found in Taheri (2019).

Optic sensors have been also developed for corrosion monitoring. Apart from measuring pH and chloride concentration, optical fiber sensors can also monitor corrosion through the measurement of strain, temperature or change in the refractive index of the fibers. The sensors based on measurement of strain and temperature have a longer life than the sensors based on measurement of refractive index, concentration of chloride ions, and pH. However, the sensors with a short life may have a high sensitivity to corrosion at an early stage.

Initially, FBG have been used for corrosion detection based on the change in the fluorescence intensity of the sensor with the change in pH and also in the change of strain due to the corrosion (Das et al. 2018). However, not only FBG are available for discrete monitoring of corrosion effects. Fan and Bao (2021) presents a comprehensive review of representative types of fiber optic sensors for monitoring corrosion in reinforced concrete. The reviewed types of sensors include grating sensors, interferometer sensors, distributed sensors, and reflectometer sensors. Most of the FBG-based sensors have been checked in laboratory environment and therefore, there is still a need to further investigate their performance in the reinforced concrete under real conditions.

Long period grating (LPG) sensors are sensitive to the refractive index of the surrounding medium (not only of core and cladding) or environment, enabling monitoring of corrosion. LPG is sensitive to multiple variables such as strain and temperature in addition to refractive index, therefore multiple sensors are needed for compensation of strain and temperature changes. Besides, LPG is sensitive to bending, which therefore should be avoided in the application of LPG sensors. Regarding the most suitable OF corrosion sensor for a specific application, it should be pointed out that most of the developed sensors are only suitable for the corrosion propagation stage. The LPG sensor that measures the chloride concentration and the spectrometer that measures the chloride concentration or pH are suitable to monitor corrosion in the initiation and the onset stage, although they are inapplicable in the corrosion propagation stage.

DOFS have been also used to develop corrosion sensors. Fan et al. (2020) built up a helix pattern made with DOFS deployed around the steel bar to measure expansive strains generated by corrosion of the steel bar (Figure 2.13). The strain measured from the sensor was utilized to evaluate the volume of the corrosion products surrounding the steel bars, the mass loss in the reinforcement due to corrosion and predict the cracking of the concrete cover.



(a) (b)

Figure 2.13: Reinforced concrete beams: (a) before concrete casting; (b) after the accelerated corrosion test (Fan et al. 2020)

Abbas et al. (2015) presents a sensor for measuring the chloride ions in concrete structures using a wireless system. A reliable and continuous measurement of chloride ions is achieved by embedding a sensor (Ag/AgCl electrode) inside concrete measuring wirelessly its half-cell potential. The sensor does not need external power. Zhou et al (2017) presents a similar self-powered and wireless sensor for monitoring chloride ions. The measurement results indicate that the proposed passive sensor can achieve a reliable communication distance of 16.3m and can reliably measure the chloride ion concentration in concrete.

2.2.2.8 Acoustic emission sensors

The dynamic perturbation caused by sudden growth in defects, e.g. fatigue crack growth, releases elastic waves, which are converted by Acoustic Emission (AE) sensors attached on the structure surface to electrical signal. AE technique has been studied for assessing damage progression and localization in concrete and metallic structures. Acoustic emission sensors can be deployed in metallic, concrete, and composite materials (Saravanakumar et al. 2021). The sensors used in AE are usually of piezoelectric type, but also optical fibers in the form of FBG can be deployed when ultrasonic signals are of interest. Fiber-based distributed acoustic sensors (DAS) are another sensor suitable technique for acoustic emission monitoring. The required frequency of AE detection may reach megahertz. Furthermore, real-time detection is needed in these sensors since the AE signals cannot be repeated. In this sense, DAS face resolution and sensitivity issues in acoustic emission when signals have high frequencies. On the other hand, AE detection using FBG has become more realistic after the emergence of the PSFBG-based ultrasonic sensor (Wu et al. 2018).

Thirumalaiselvi and Sasmal (2021) uses unsupervised (k-means clustering) and supervised (support vector machines (SVM)) pattern recognition algorithms to classify the AE signal dataset recorded at different damage stages. The study found that SVM can effectively classify two types of AE sources appropriately, enabling the potential application of AE technique for initiation of cracking and its progression. The proposed pattern recognition supported acoustic emission-based methodology can distinguish between cracks that are new from cracks that are growing. Therefore, the method can be very effective in condition monitoring of in-service structures where the information of the health of the structure can be automatically and continuously assessed through the emitted acoustic signals from formation of micro-cracks.

Olaszek et al. (2016) and Tonelli et al. (2020) have shown the successful application of this technique in detecting damage and the occurrence of cracking to the case of a prestressed concrete bridge and a prestressed concrete beam extracted from an existing viaduct, both loaded up to failure.

A main problem in the acoustic emission technology is the low SNR (signal to noise ratio), which is enhanced by the length of the coaxial cables traditionally used by AE instrumentation. To overcome this situation, the idea is to closely locate the sensor and a signal amplifier, providing a new capability to process signals in close proximity to AE transducers at the inspected facility and also creating low-cost and low-weight sensor nodes (Bogomolov et al. 2021).

Monitoring the structures in service using AE can be long-term, and the amount of data obtained and handling it is another subject of consideration. Alver et al. (2021) present some of the methods and strategies to overcome this problem. As the data rate of AE method can be significant and the method requires real time data collection in 24/7 from multi-channel systems, it is important to develop effective methods to handle big data and interpret the results in a timely manner. The data size can be reduced by applying principal component analysis. The industrial Internet of Things (IIoT) provides a way to address big data issue in SHM. IIoT in AE integrates sensor output with real-time edge processing algorithms that make faster decision making without transferring data to the base station (Asif et al. 2020)

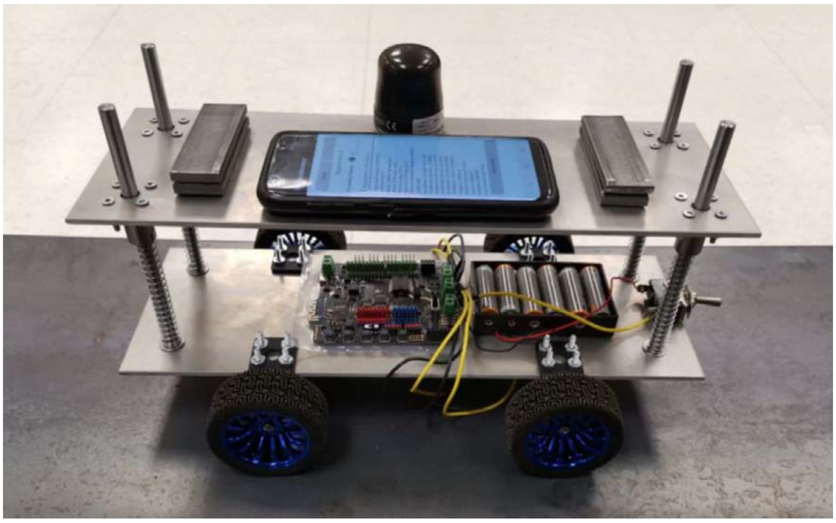
2.2.2.9 Sensing Sheets

Yao and Glisic (2015) present the sensor technologies based on Large Area Electronics (LAE) which enable direct sensing and can be scaled to the level required for Structural Health Monitoring (SHM) of civil structures and infrastructure. Sensing sheets based on LAE contain dense arrangements of thin-film sensors, associated electronics and various control circuits deposited and integrated on a flexible polyimide substrate that can cover large areas of structures. The sensors that can be incorporated in the sheet are strain, pressure, temperature and humidity sensors. The piezoelectric elements are the most used strain sensors. The strain sensing can be considered as a two-dimensional (2D) quasi-distributed sensor.

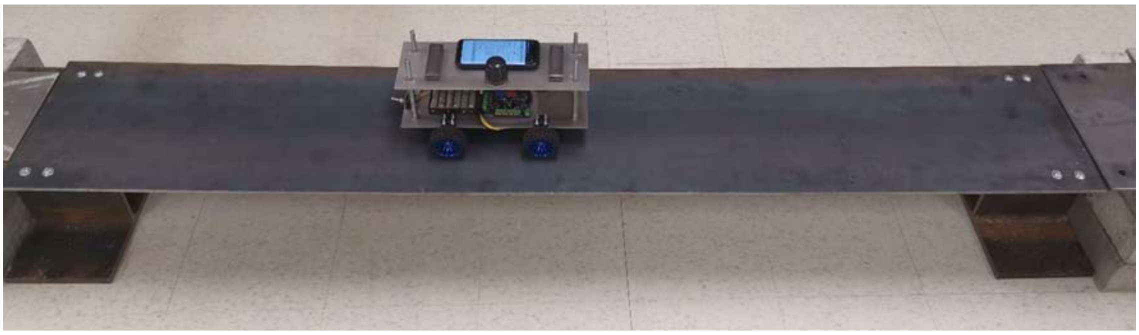
Loupos et al. (2017) show the development of a dielectric-elastomer and micro-electronics-based skin-like sensing that may offer spatial sensing of reversible (repeated) strains in the range of 0.012% to more than 10%, that requires little power to operate, is easy to install on an irregular surface, is low cost compared to existing sensors, allows simple signal processing, and includes the ability of self-monitoring and self-reporting. The system is integrated on a fully distributed and autonomous wireless sensor network that can self-monitor.

2.2.2.10 Smartphones

Smartphones can provide crowd-sensing data. They may include several sensors as accelerometer, gyroscope, cameras, microphones, proximity sensors and GPS, which could be used in the monitoring of different structural parameters (Mei and Gül 2019, Morgenthal et al. 2018). Several studies have shown that smartphones could be used as reliable sensors to collect acceleration data and apply them into indirect health monitoring techniques to assess structural condition (Feng M. et al. 2015). In the case of the application to bridge drive-by monitoring, the conclusion is that the recorded vibration of the vehicle is highly dominated by vehicle characteristics, such as suspension, mass, and speed. Shirzad-Ghaleroudkhani et al. (2020) used a smartphone to detect multiple damage states on a lab-scale bridge model. They showed that the damage and boundary conditions in the bridge model could be identified using the smartphone on a car model even if the speed, weight, and suspension of the car were varied between experiments. It was demonstrated how by using a large set of passing cars with different features, the fundamental frequency of the bridge was captured. To collect the acceleration from the car, one smartphone, a Samsung Galaxy S8 (Samsung Electronics, Seoul, South Korea), with a sampling frequency of 400 Hz was used as seen in Figure 2.14.



(a)



(b)

Figure.2.14: a) View of the smartphone on the vehicle. b) the car passing the scale bridge (Shirzad-Ghaleroudkhani et al. 2020)

Morgenthal et al. (2018) used a microcontroller-based system and smartphone systems to measure vibrations on stays of cable-stayed bridges and identify frequencies sufficiently accurately even under ambient wind excitations. They concluded that the best system to obtain highly accurate force measurements is the RPi microcomputer (an external single-board computer called Raspberry Pi (RPi; Raspberry Pi Foundation, Cambridge, U.K.)) connected with an external sensor and the smartphone acting as a central control unit.

The first challenge on using mobile phone sensing is the large-scale of devices within the structure, resulting in a huge amount of data traffic, which may overwhelm the network resources. Therefore, some techniques must be employed to reduce the amount of data traffic. This can be achieved by local data aggregation and processing on mobile devices and smart phones. The second challenge is the data accuracy. Mobile devices and smart phones are equipped with different types of sensors from different manufacturers; hence, sensors vary significantly in their sensitivity and noise. Thus, there is a need to improve data accuracy by identifying devices that are likely to produce accurate sensed data, performing global centralized data aggregation, and considering the spatio-temporal mobility patterns of the users.

2.2.3 DATA LOGGERS

A data logger is an electronic device that records data over time either with a built in instrument or sensor or via external instruments and sensors. They are based on a digital processor (or computer) and called digital data loggers (DDL). In general, they are small, battery-powered, portable, and equipped with a microprocessor, internal memory for data storage, and sensors. Some data loggers interface with a personal computer, and use software to activate the data logger to view and analyze the collected data, while others have a local interface device and can be used as a stand-alone device.

One of the primary benefits of using data loggers is the ability to continuously collect data on a 24-hour basis. Upon activation, data loggers are typically deployed and left unattended to measure and record information for the duration of the monitoring period.

Data logging and data acquisition are different concepts. A data logger is a data acquisition system, but a data acquisition system is not necessarily a data logger. Data loggers typically have slower sample rates. A maximum sample rate of 1 Hz may be considered to be very fast for a data logger. Data loggers are implicitly stand-alone devices. The unattended and remote nature of many data logger applications implies the need in some applications to operate from a DC power source. This unattended nature also dictates that data loggers must be extremely reliable since they may operate for long periods nonstop with little or no human supervision and may be installed in harsh or remote locations. The original model of a stand-alone data logger is changing to one of a device that collects data but also has access to wireless communications for alarming of events, automatic reporting of data and remote control. Data loggers are beginning to serve web pages for current readings, e-mail their alarms and FTP their daily results into databases or direct to the users.

The monitoring frequency, type of sensor, and the method to retrieve data will lead to the selection of a suitable data-logger and telemetry system.

2.3 REMOTE SENSING TECHNOLOGIES

2.3.1 INTRODUCTION

Remote sensing is the process of acquiring the physical 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 collecting a wide variety of physical characteristics. Position, velocity, temperature, or variation of elastic properties throughout a medium represent some of the potential inferred representations of the asset. Typically, satellites, aircrafts or other ground base stations are provided with special data-gathering devices for collecting remotely manifold information. This helps researchers "sense" things about nature and/or the built environment from a certain distance. Some examples are:

- Space or shuttle cameras on satellites and airplanes take images of large areas on the Earth's surface. These images allow covering wide regions and allow gathering meaningful information at such levels. These images can be used for detecting many alterations on the ground’s Earth, i.e., subsidence.

- Radio waves. With applications ranging from astronomy to communication, by studying the radio waves originating from many sources, one can learn about the target composition, structure, and motion.

- Sonar systems techniques are used to detect the scour profile in piers of bridges founded in rivers or in quays of harbors. Ships generate acoustic emissions that can be used to create images of the ocean floor without needing to travel to the bottom of the ocean.

- High-definition surveying (HDS), or “laser scanning,” is often used to capture a highly detailed 3D image of natural landslides or assets belonging to the built environment.

- Electromagnetic radiations are emitted by radars as geophysical methods to image the subsurface. Non-intrusive method of surveying the sub-surface allow investigating underground utilities such as concrete, asphalt, metals, pipes, cables, or masonry.

It is worth pointing out that these techniques are of a great versatility for condition monitoring and survey. Maintenance strategies often rely on such technologies. In most cases, these technologies are cost-effective since it is possible to gather a larger amount of data than from sensors located at specific positions. However, their automated integration within BIM environments and subsequently within Digital Twins is yet to come. In the following subsections, a review on the use of such technologies in the realm of maintenance of assets of the built environment are discussed together with examples presented in the academic literature.

2.3.2 POINT CLOUD

Three-dimensional scanning is a technique used to analyze and capture the shape of a real-world 3D objects. The result is a computer-readable 3D collection of points, which can be saved, edited, and even 3D-printed. Nowadays, the increasing need for continuous inspections of existing infrastructure and the advent of the digital twin era require the development of improved non-invasive data acquisition techniques. Born in the field of geomatics, the use of terrestrial laser scanners and photogrammetry provide dense and accurate geometric information in the form of point clouds. A point cloud is an unstructured and unordered collection of 3 dimensional points in a coordinate frame of reference (x,y,z) which normally represent the external surface of an object. Depending on the 3D scanning device, points include additional information as colour (RGB) or intensity information. Point clouds are increasingly being applied in multiple fields within the construction industry, including geometric inspection, 3D models generation, and structural health monitoring (Wang and Kim 2019).

2.3.2.1 Laser Scanners

Laser scanners, also referred as LiDAR (Light Detection And Ranging) are devices that emit narrow, intense beams of coherent monochromatic light for measuring distances to objects. Measurements recorded with laser scanners are generally based in two principles: Time-of-flight and Phase-shift. Scanners using time-of-flight (ToF) principle emit light pulses that are reflected back by objects into the measurement device (Lemmens 2011). Distance is calculated by multiplying the travel time by the speed of light divided by 2. Scanners using phase-shift (PS) principle continuously emit sine-modulated waves. The phase of the emitted wave is compared with the phase of the wave received back, and the distance is calculated from the phase difference.

The PS principle allow the laser to record high accuracy, ultra-fast data at a medium range (350 m), while the ToF technique allow to reach longer ranges (km), at a slightly lower rate and with slightly less accuracy. Laser scanning devices usually integrate the LiDAR unit with an opto-mechanical scanner which position, and orientation is accurately determined e.g. by a GNSS and an inertial measurement unit (IMU) (Lindenbergh 2019). Measurements at different azimuths and elevations produce a point defined by its polar coordinates, which can subsequently be transformed into the cartesian system.

Terrestrial Laser Scanning (TLS) is the most popular device to perform 3D scans. It can be fixed on or next to a construction for real-time monitoring, but it is usually restricted by a blocked sightline between devices and targets. Therefore, capturing all scanner targets requires multiple scans from different viewpoints that are subsequently merged into a unified point cloud (registration process). For that reason, planning for scan (P4S) is needed to obtain quality point clouds, avoid redundancy in data and optimize scan duration. Aryan et.al (2021) presents a review of scan planning optimization methods and quality criteria, namely, the level of completeness (LoC), accuracy (LoA), resolution (LoD) and registrability of the point cloud, to benchmark data quality requirements for specific targets and applications. Mobile Mapping Systems (MMS) gains popularity as a solution to mobility constraints of TLS. MMS generally includes land vehicles and Unmanned Aerial Vehicles (UAVs) which are equipped with redundant positioning and orientation sensors (odometers, cameras and IMUs) that are integrated along with GNSS and IMU used in fixed scanning systems (Lemmens 2011).

Raw point cloud data is unorganized, disordered and only single-point information can be accessed. Therefore, point clouds need to be submitted to a set of computational procedures to abstract useful geometrical information. For that purpose, data cleansing, data registration, data segmentation and object recognition are identified as the main point cloud processing steps as presented in Figure 2.15 (Wang et al. 2020).

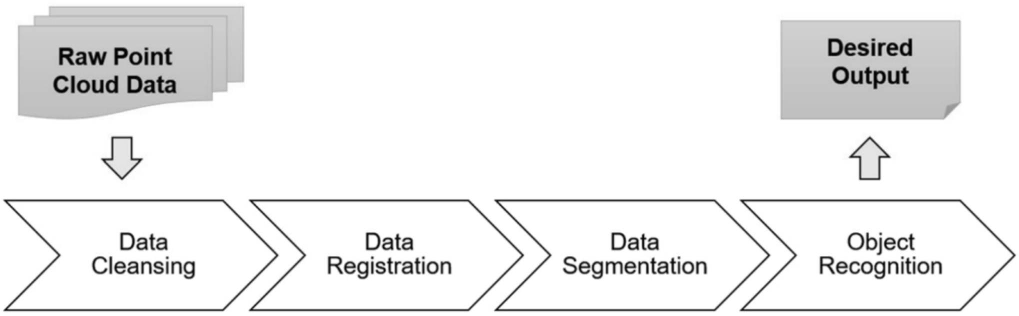


Figure.2.15: Point Cloud Analysis (Wang et al. 2020)

Depending on the sensor physical limitation and the complexity of the scan environment and targets, raw point cloud data might contain various types of outliers, poorly scanned areas and shadows (gaps). Thus, a pre-processing step for data preparation and cleansing is necessary to set data ready for subsequent processing steps. Rashidi and Brilakis (2016) proposed a method for data preparation based on three steps, i.e., outlier removal, gap filling and density balancing, providing reviewed criteria to perform each step.

Generally, criteria for outlier removal are based on the information of the neighbourhood points. Most popular methods are based on parametric factors, namely, Distance-to-plane factor: a point is considered an outlier if its distance to a plane fitted to its k-nearest neighbours exceeds a certain threshold; Spherical distance factor: the point is considered an outlier if the diameter of a sphere including its k-nearest neighbours exceeds a certain threshold; K-nearest-neighbour reciprocity factor: outliers are identified using reciprocal inclusion on k-neighbouring of vicinity points (Rashidi and Brilakis, 2016). Other outlier filtering approaches as statistical outlier removal (SOR), spatial frequency (SF) filters and morphological filters are commonly used too (Carrihlo et al., 2018). Gap-filling methods have been developed to compensate data lags due to constrained scanning positioning and object sight occlusions, becoming an essential step in 3D reconstruction. Guo et al. (2018)reviewed existing algorithms for hole filling , which describe volume and surface-based methods conducted on point clouds or meshes.

Point cloud registration is defined as the process of finding the spatial transformation for aligning two or more-point clouds into the same reference system (Figure 2.16). Registration is used for full geometric reconstruction of specific targets when they are scanned from different positions, fitting scans to existing CAD models, recognizing 3D objects within the scanned scene (recognition-by-fitting) and aligning scans from the same target taken by different acquisition systems or at different times (Castellani and Bartoli 2020)

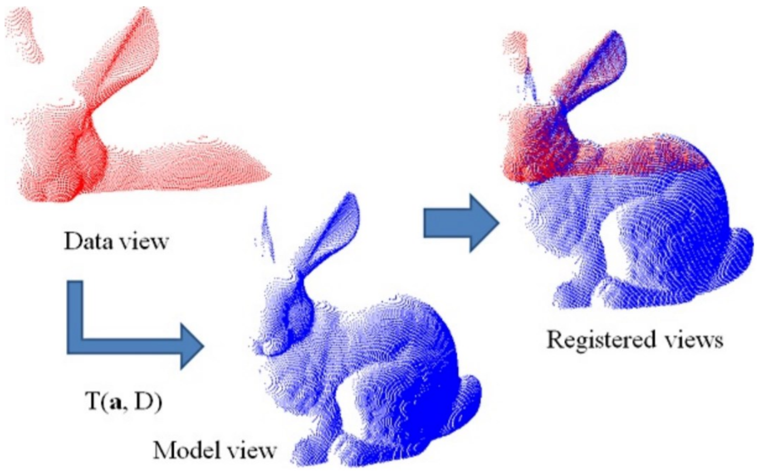
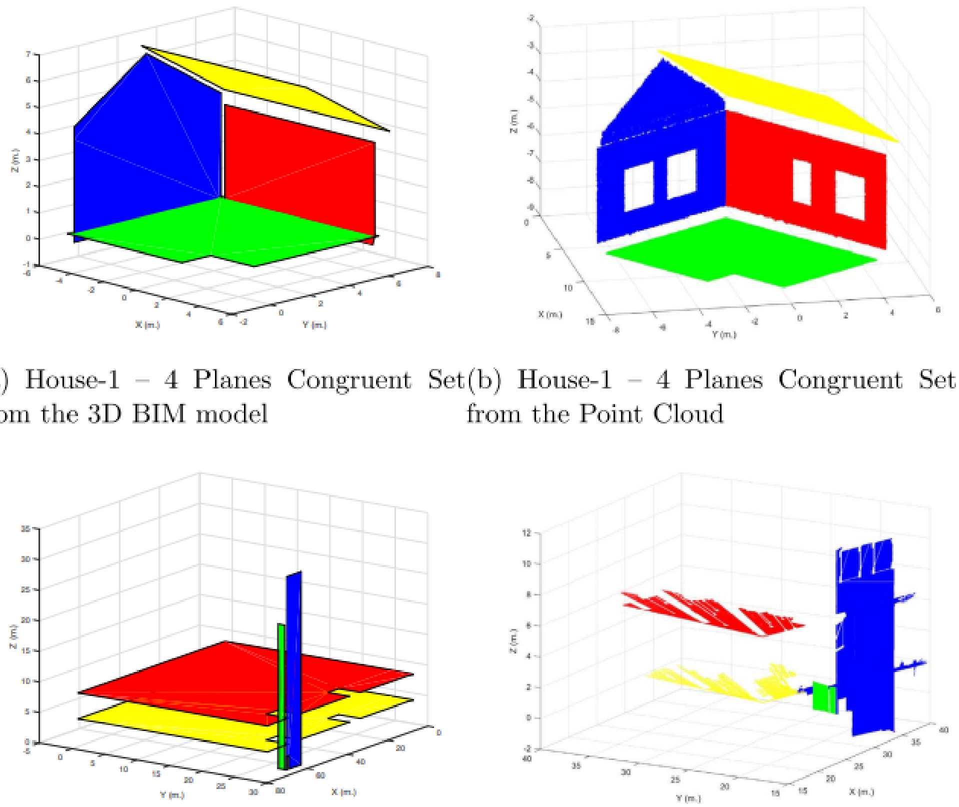


Figure.2.16: Point Cloud Analysis (Castellani and Bartoli 2020)

Registration methods can be classified into two categories: fine (or local) registration and coarse (or global) registration.

The most commonly used method for fine registration is the Iterative Closest Points (ICP) algorithm (Besl and McKay 1992). However, ICP-based only performs well when the two-point clouds are close enough to each other since the optimization function can easily find local minima that do not correspond to correct alignments. Additionally, most of these methods are very susceptible to the presence of outliers, that could distort the optimization results (Castellani and Bartoli 2020). Therefore, a common practice is to divide the registration procedure into two steps: first, a less accurate registration method is performed to roughly align the geometries, and then ICP-based methods are used to improve the initial alignment.

Coarse registration is a widely studied problem, especially for fitting captured point clouds with existing geometrical models. A common practice is performing manual alignment between point clouds using point correspondences obtained placing visual targets in the scan site. However, this work can easily become tedious when managing large data sets. Then, automated coarse registration study field has gained importance and several approaches have been taken in the last decade. A common approach for automated coarse registration is the usage of geometric descriptors in both point clouds, which are normally computed from the geometrical characteristics of the point neighbourhood, and then used to perform the registration (Rusu et al. 2008, Rusu et al. 2009). Another approach is identifying key-points in both point clouds, normally computed from geometric descriptors formerly mentioned (Allaire et al. 2008, Trzcinski et al. 2013). Aiger et al. (2008) proposed a registration approach that is based on 4-Point Congruent Set (4-PCS) algorithm. The algorithm and its improved variants (Theiler et al. 2014, Mellado et al. 2014) use key-points to calculate congruent 4-point bases and choose the best transformation between pair of bases that minimizes distance between point clouds. Despite 4-PCS supposed a great advance to the automated coarse registration problem, the built environment present high levels of symmetry, occluded data and clutter that might lead these algorithms to be ineffective. However, some authors are taking advantage of these as-built characteristics to developed new registration algorithms. Bueno et. Al (2018) developed a 4-plane congruent set (4-PICS), inspired in 4-PCS algorithm, which take advantage of the great number of planar elements that are normally found in the built environment (Figure 2.17). The algorithm is robust; however, computation time might be considerable for large datasets.



(a) House-1 – 4 Planes Congruent Set from the 3D BIM model

(b) House-1 – 4 Planes Congruent Set from the Point Cloud

(c) UW-E5 – 4 Planes Congruent Set from the 3D BIM model

(d) UW-E5 – 4 Planes Congruent Set from the Point Cloud

Figure.2.17: 4-plane congruent registration example (Bueno et al. 2018)

Once registration is performed, points forming the final point cloud need to be classified into regions defined by specific geometric characteristics. Points that share geometric features are equally labelled and then grouped into continuous regions, forming segments. Several segmentation methodologies are proposed in literature. Nguyen and Le (2013) and posteriorly Wang et al. (2019) present through review of such methods and classify segmentation methods into 5 categories: Attribute-based, edge-based, region-based and graph-based.

Attribute-based methods directly cluster points basing on geometric features either computed from point neighbourhood (e.g., normal, curvature…) or provided by the scanner device (reflectance, colour). These methods are easy to understand and implement, however, their results rely on neighbouring points, thus being sensitive to the presence of noise.

Edge-based methods detect boundaries of regions in the point cloud and obtain segments by allocating points within those boundaries. The principle for boundary detection is to identify points with rapid density changes. Common parameters used for boundary detection are curvature, normal, gradients and higher order derivatives. Despite these methods present a fast segmentation, they are sensitive to noise and uneven point cloud density.

Region-based methods can be classified into seeded and unseeded methods. Seeded methods start the segmentation process at random seed points, from which the region will grow adding neighbouring point if certain criteria are met. Seeded methods are highly dependent on initial seed points and the criteria used to add point to regions, which could lead to under/over-segmentation. On the other hand, unseeded methods include all points in a single region, and then start subdividing. Determining the division criteria is a challenging task in these methods, which need a large amount of prior knowledge needed (region models, number of regions, etc). In general, region-based methods are more robust than edge methods, but they have problems determining region boundaries, leading to over or under-segmentation.

Graph-based methods consider the point cloud in terms of a graph model. Compared to other methods, graph-based methods provide better performance in segmenting complex point clouds, also in the presence of noise and uneven density distribution. However, most of these methods need to be pre-trained or need special co-registered sensors to function.

Model-based methods rely on the principle that complex objects can be decomposed into simple geometric primitives that can be mathematically fitted to point cloud regions. Most model fitting approaches are based on the Hough Transform (HT) and in Random Sample Consensus (RANSAC). As these approaches are purely mathematical, they provide robust and fast segmentation against outliers. RANSAC is also able to process large point cloud data sets. However, their accuracy is limited when dealing with multiple point cloud sources (Wang et al. 2019).

To generate semantically rich 3D models, another layer of abstraction is needed, where segments or single points are grouped and labelled into object classes, instances, and relations among them (Tang et al. 2010). In the construction industry, these labels are generally associated to BIM elements such as walls, floors, roofs, pipes, columns, beams, etc. Some of these objects can be directly recognized by simply generating a library of geometrical features from CAD/BIM objects that clearly identify objects that are known to be present in the scene. This method is useful for easily identifying pipe installation using their local curvature as a shape descriptor (Czerniawski et al., 2016). The rest of elements are usually identified using human-codified algorithms based on previous knowledge referred to identifiable semantic features such as size, position, orientation, topology, and density of the objects within the point cloud (Pu and Vosselman, 2009). Despite that these methods can be effective and easy to implement, they are very specific to the use case and are limited to be used with simple geometries. Scan-vs-BIM methods can also be developed to identify objects within the scanned scene by projecting the points onto CAD/BIM models which have been previously co-registered (Bosché et al. 2015). Actually, most research regarding object recognition techniques is pointing towards the use of supervised and unsupervised deep learning methods, as is described in the following section.

Deep learning has already become the most powerful data processing tool for computer vision, successfully performing classification, segmentation, and object recognition tasks, mostly due to a wide development of Convolutional Neural Networks (CNN) (See chapter 2.1.2). 3D point clouds could be understood as 2D images with additional 3D spatial information, however, the irregularities in point density distribution and the lack of structure and order prevent from directly adapting computer vision deep learning techniques, which are performed implemented over ordered, regular and grid-structured data inputs. Research has taken two different approaches to overcome this challenge: converting the point clouds into a structured grid format and developing new deep learning approaches to use the raw point as an input (Bello et al. 2020).

Approaches to structure point clouds can be broadly classified in two groups: voxel-based approaches and multi-view approaches. Voxel-based methods convert point clouds into a grid of fix-sized voxels where 3D CNNs can be applied. 3D shapeNets (Wu et al. 2015), VoxNet (Maturana and Scherer 2015) and OctNet (Riegler et al. 2017) are representative for this approach. Multi-view approaches take advantage of the already matured 2D CNNs by converting point clouds in a collection of 2D images. A representative example of these approaches are MultiviewCNNs (Su et al. 2015) with improvements like using optimum viewpoint selection (Kanezaki et al.2018) and multi-resolution methods (Qi et al. 2016).

Approaches for processing raw point clouds using deep learning are being increasingly developed since the release of PointNet (Qi et al., 2017a,b), which has served as a foundation for the development of many supervised and unsupervised (autoencoders) point-based methods, which have been extensively reviewed (Liu et al.2019, Bello et al. 2020)

In the construction industry deep learning approaches have been mainly used in semantic segmentation of as-built facilities. Perez-Perez et al. (2021) proposed a new deep learning architecture called Scan2BIM-NET, for semantically segmenting BIM elements such as floors, ceilings, beams, columns and pipes in industrial facilities. Pierdicca et al. (2020)proposed a Scan-to-BIM semantic segmentation on cultural heritage based on an improved Dynamic Graph for Convolutional Neural Network (DGCNN) by adding extra features like normals and colours. In bridge engineering, Kim and Kim (2020) successfully performed automated bridge component segmentation using PointNet architectures introducing subspace partitions of the bridge location. They also compared PointCNN, DGCNN and PointNet to classify the components of bridges, showing higher accuracy in DGCNN since it can learn point relations with surrounding elements. Taking advantage of the classification opportunities provided by the DGCNN, the same authors proposed an automatic BIM modelling from point clouds with incomplete scanned elements, achieving a 99% of complete elements modelled (Kim,and Kim 2021). Lee et al. (2021) proposed an improved Hierarchical DGCNN (HGCNN) based on PointNet and DGCNN for segmenting railway bridge components which presented increased accuracy, specially for bridges with tall elements such as electric poles. Generally, the lack of training data sets is highlighted as one of the main limitations in deep learning approaches for the construction industry. Therefore, the generation of useful synthetic data from existing BIM models (Ma et al. 2020) and the development of efficient and accurate models that need reduced training data (Xia et al., 2022) might be useful considerations for future approaches.

Detailed geometrical information provided by 3D point clouds is being applied for structural health monitoring applications, including beam analysis, structural inspection, and Finite Element Method calibration.

Surveying historical structures using point cloud-based methods are effective for evaluating their structural health. Korumaz et al. (2017) proposed a methodology in which point cloud data was used to perform deviation analysis and FE modelling of heritage buildings. The method was applied in a medieval period brick minaret. Mesh and solid models were generated from the point cloud data. Solid models allowed the calculation of surface imperfections, degree of inclination of the structure with respect to the vertical while meshes were used in FE analysis software to perform modal and push-over analyses Sánchez-Rodríguez et al. (2018) used a method to detect structural faults on masonry bridges. The method first segmented the bridge to identify its piers and their faces, and then parametrized their pose using elevation and azimuth angles obtained from PCA (Figure 2.18). Depending on the relative pose of pier faces, multiple damages can be assessed.

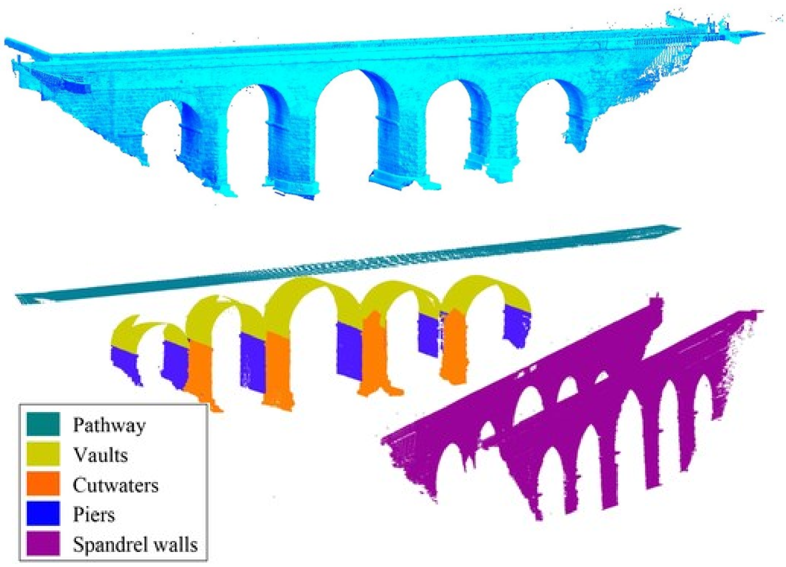


Figure.2.18: Bridge segmentation and piers identification (Sanchez-Rodríguez et.al. 2018).

Sánchez-Aparicio et al. (2014) perform a full geometric characterization of the Saint Torcato church (Portugal) combining TLS and UAV SfM (Figure 2.19). The hybrid point cloud was converted to CAD using parametric features and NURBS for complex geometries. After CAD modelling, crack detection could be performed using digital image processing on the images overlapped with the point cloud. Additionally, a FE model was generated and calibrated using modal analysis to be compared with previous acceleration data.

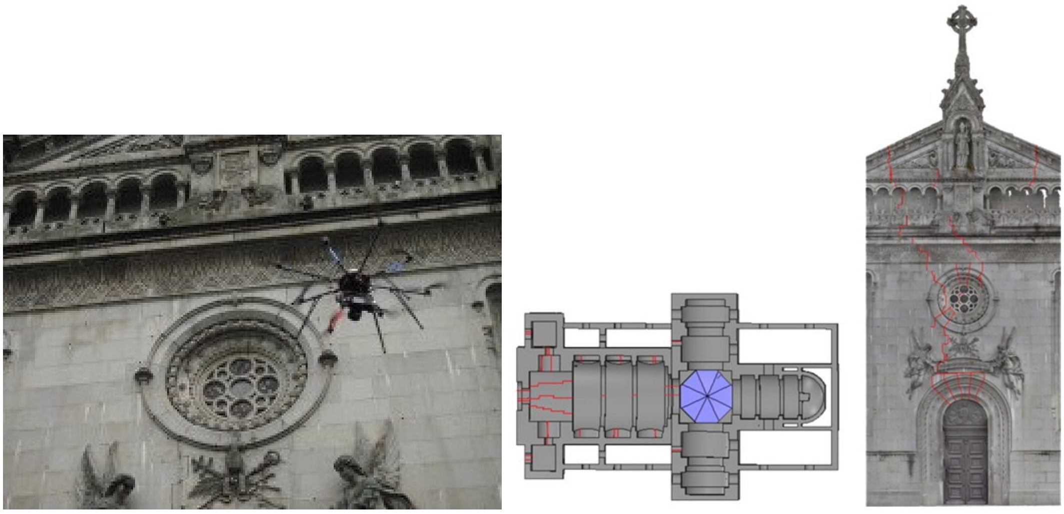


Figure.2.19: Photogrammetric point cloud acquisitions and crack detection (Sánchez-Aparicio et al. 2014).

For bridge inspection, Artese and Zinno (2020)used a terrestrial laser scanner to scan a single straight line under a bridge to obtain the dynamic deformation when a dynamic load is applied during a load test as shown in Figure 2.120. 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 measurement to estimate the behaviour of structures.

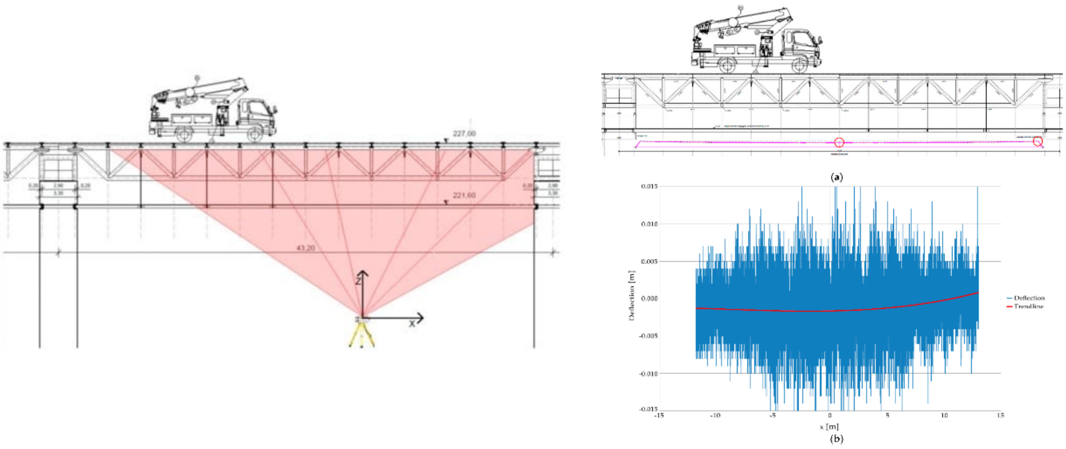


Figure.2.20: Scanning scheme and deflection interpolation (Artese and Zinno 2020)

Similarly, Riveiro et.al. (2012) and Riveiro et al. (2013) validated the use of laser scanner and photogrammetry to perform routine bridge inspections of the minimum vertical under-clearance. The lower surface of the bridge was interpolated using 4th

degree polynomials and its distance to the ground-plane was calculated. Cha et al. (2019)conducted deformation analysis using shape deformation model from the point cloud extracted from a bridge (Figure 2.21). The model consists of a voxel grid generated from the point cloud compressed using an octree data structure . This allows efficient management of the data. Deformation between multiple octrees is calculated using the Hausdorff distance.

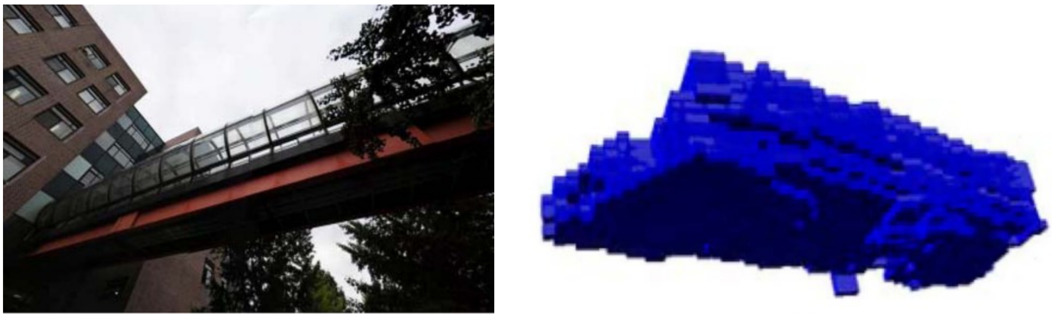


Figure.2.21: Bridge voxelization (Cha et.al, 2019)

Results showed considerable agreement with LVDT measurements when the deflection is not smaller than the resolution of the octree. Later, the octree method was verified in laboratory using multiple specimens (Cha et al. 2020). Erdélyi et al. (2017) and Erdélyi et al. (2020) conducted geometry-based deformation analysis based on regression plane modelling using RANSAC for specific fenced parts of the bridge, monitoring the descend of the de centroid of the fenced planes obtaining accurate deformation shapes

Point cloud data has been used in laboratory test to verify its effectivity to monitor steel and concrete beam deformation. Cabaleiro et. al. (2015) designed a novel algorithm to automatically obtain deformations in steel beams subjected to bending and torsional loading using Lidar data. The algorithm fitted surface slices to segmented beam flanges. Twist and bending information were calculated using the variation of the normal angle of each slice against a straight theoretical beam without deformation. The proposed methodology also allowed to allocate maximum stress positions. Same authors proposed an alternative method using Bivariate polynomial surface fitting based on Bernoulli beam theory with torsional effects (Cabaleiro et al. 2016). The method allowed to conduct deformation verifications, as well as realistic 3D modelling of the deformed beam (Figure 2.22).

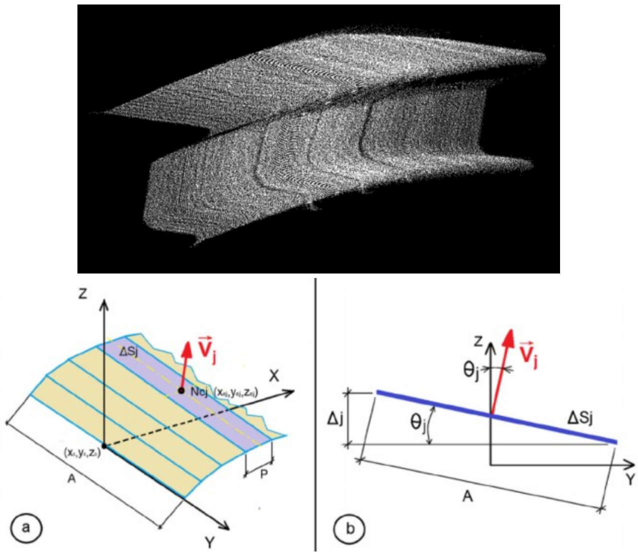


Figure.2.22: Scanned I-shaped beam polysurface fitting and twist angle calculation (Cabaleiro et al. 2015)

Mistretta et al. (2019) evaluated deformations on reinforced concrete beams measured using close-range photogrammetry based on Structure from Motion (SfM) and were compared to TLS measurements during a bending load test. Comparison between point clouds was stablished using mesh-to-mesh and modelling approaches, showing minimum errors below 1mm. The study concluded that both, TLS and Close Range Photogrammetry (CRP) are suitable methods for evaluating structural deformations, however, CRP has clear advantages in equipment costs.

2.3.2.2 Radars

RADAR is a short form for Radio Detection and Ranging systems. The basic working principle of all the radio systems is the same. The radio uses a transmitter to produce an electromagnetic signal that is then propagated into the space using an antenna. When this signal strikes an object, it gets reflected back, and this reflected signal is known to be the echo signal. When the antenna detects the echo signal, it gets fed into the receiver. The receiver then processes the echoed signal to get useful data out of it. Signals are often noise filtered. The output from the receiver passes to user-defined threshold decision systems. For finding the range of the object, the system uses the time taken by the signal to get reflected. For the target location, an angle is calculated from the direction of the echo signal to the direction where the antenna is pointing. For moving objects, the Doppler Effect is used to calculate the speed and range of such object.

The use of radars nowadays is vast. From weather predictions to aerospace, radars provide a continuous stream of data in manifold applications. Waves are characterized as pulsar or continuous. From the perspective of the use of radars with maintenance purposes of assets within the built environment, specific technologies apply. The discussion herein is focused on these technologies only.

- Space borne synthetic Aperture Radar. SB-SAR
- Ground-based synthetic Aperture Radar. GB-SAR

Space borne Synthetic Aperture Radar

SAR has got a broad range of applications. For space borne remote sensing, earth observing satellites are currently in operation. These satellites have imaging sensors working in different spectral areas. Optical, infrared or radio waves are often used. Radio waves are robust when it comes to weather conditions. The usage of optical sensors depends not only on daylight but also on the actual weather conditions. Clouds and heavy rain are impenetrable for this wavelength. Infrared sensors which are applicable day and night are even more sensitive on weather conditions. Consequently, radar sensors represent a completion of the sensor collection for remote sensing. Synthetic Aperture Radar is a remote sensing method that allows high-resolution ground surveillance by combining (synthesizing) the return echoes of radar pulses emitted from a rapidly moving observation platform.

Beyond the overall availability of SAR images there are further pros for the utilization of radar. The coherent nature of SAR enables the user to process images of subsequent overflights for interferometric analyses.

Interferometric synthetic aperture radar, abbreviated InSAR , is a radar technique used in geodesy and remote sensing. This geodetic method uses two or more synthetic aperture radar (SAR) images to generate maps of surface deformation or digital elevation, using differences in the phase of the waves returning to the satellite or aircraft. The technique can potentially measure millimetre-scale changes in deformation over spans of days to years. It has applications for geophysical monitoring of natural hazards, for example earthquakes, volcanoes and landslides, and in structural engineering, in particular monitoring of subsidence and structural stability. Early exploitation of satellite-based InSAR included use of Seasat data in the 1980s, but the potential of the technique was expanded in the 1990s, with the launch of ERS-1 (1991), JERS-1 (1992), RADARSAT-1 and ERS-2 (1995). These platforms provided the stable, well-defined orbits and short baselines necessary for InSAR. More recently, the 11-day NASA STS-99 mission in February 2000 used a SAR antenna mounted on the space shuttle to gather data for the Shuttle Radar Topography Mission. In 2002, The European Space Agencyy ESA launched the ASAR instrument, designed as a successor to ERS, aboard Envisat. While the majority of InSAR to date has utilised the C-band sensors, recent missions such as the ALOS PALSAR, TerraSAR-X and COSMO-SkyMed are expanding the available data in the L- and X-band. Most recently, ESA launched Sentinel-1A and Sentinel-1B – two C-band sensors. Together, they provide InSAR coverage on a global scale and on a 6-day repeat cycle. The availability of such sets of data for civilian applications represent a major pivotal point for civil engineering. For instance, European data sets such as Sentinels (https://sentinels.copernicus.eu/web/sentinel/home) represents a contribution for humankind with manifold applications.

The feasibility of using spaceborne high resolution synthetic aperture radar (SAR) data to sense bridge deformations at periodic time intervals without the need to install any equipment on a bridge has been studied recently. By then, satellite-based InSAR technology was effectively implemented for long-term bridge deformation monitoring with millimeter range precision. This represents an interesting perspective for augmenting conventional inspection methods (Figure 2.23).

Figure 2.23. Aerial view of the bridges analyzed by Hoppe using satellite-based interferometric images

In Italy, as a part of an experimental campaign planned within the 2019–2021 DPC-Reluis Project, information retrieved from satellite data and on-site vibrational measurements was merged. The “Ponte della Musica–Armando Trovajoli” bridge was selected as test site (Ponzo et al. 2020). They exploited long sequences of satellite SAR acquisitions collected from ascending and descending orbits by the Italian COSMO-Skymed (CSK) constellation over the wide urban area of Rome (Figure 2.24). The available data were analyzed in a GIS Software and categorized according to structural needs.

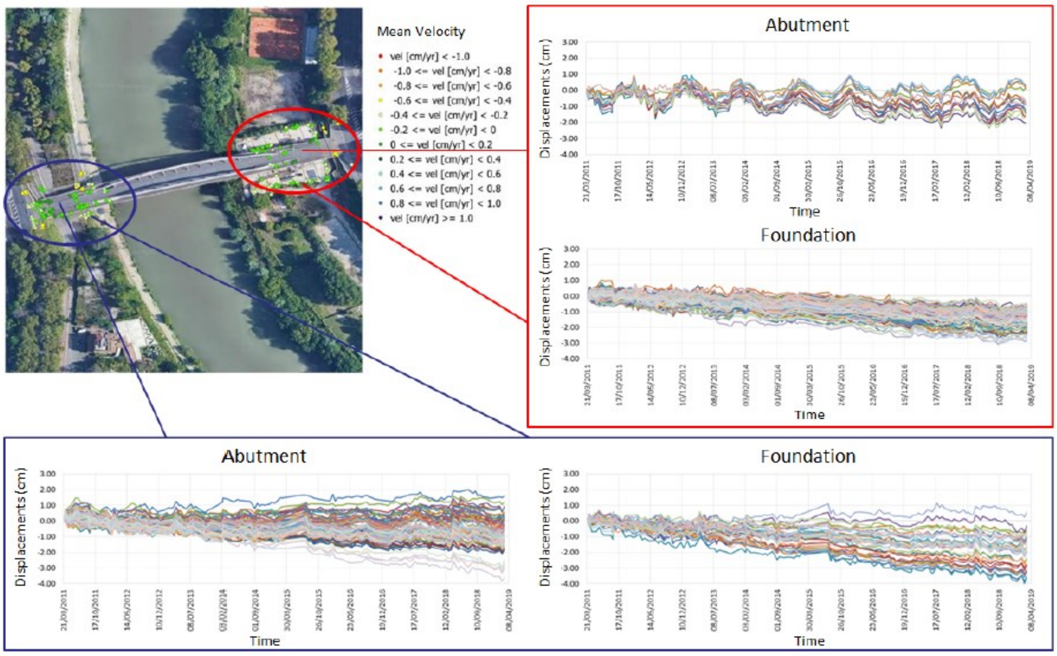


Figure 2.24. Time series for displacements. Ascending orbit (Ponzo et al. 2020).

Also in Italy, a fusion between SB-Insar (COSMO-SkyMed) and Ground Penetrating Radar for the analysis of a steel truss bridge has been presented by D’Amico et al. (2020) as shown in Figure 2.25.

Figure 2.25. PS-outcome of the InSAR data (D'Amico et al. 2020).

Recently in Hong Kong, a multi-temporal DInSAR approach for remote exploration of deformation characteristics and mechanisms of bridges was presented (Qin et al. 2019). The nature of the studied bridges was complex (cable-stayed, multi-spanned arches) and a set of damage sensitive points was identified in those assets (Figure 2.26).

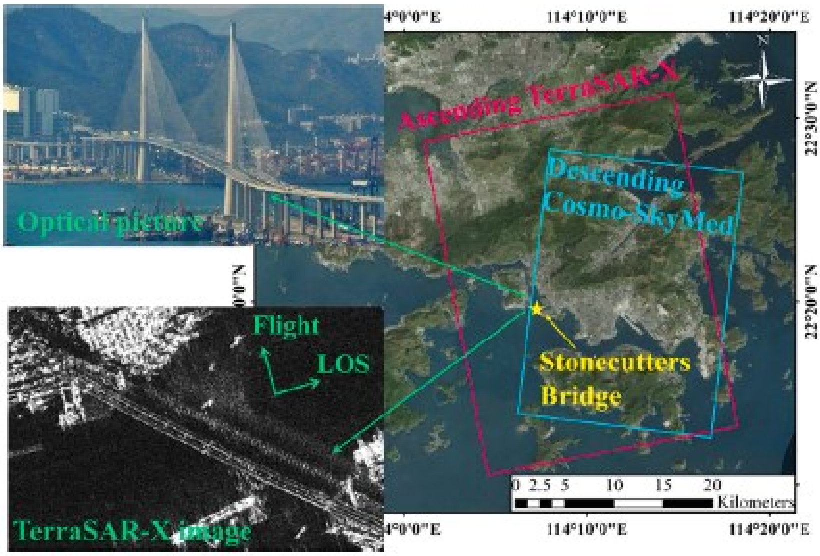


Figure 2.26. Usage of Space borne SAR for analysis of Stonecutters Bridge, Hong Kong (Qin et al. 2019).

In a nearby location, displacements of the Hong-Kong-Zhuhai-Macao bridge (HZMB) were derived using Persistent-AScatter Interfereometruc Synthetic Aperture Radar (PS-InSAR). An analysis of the time series was presented by Xiong et al (2021) quite recently (Figure 2.27).

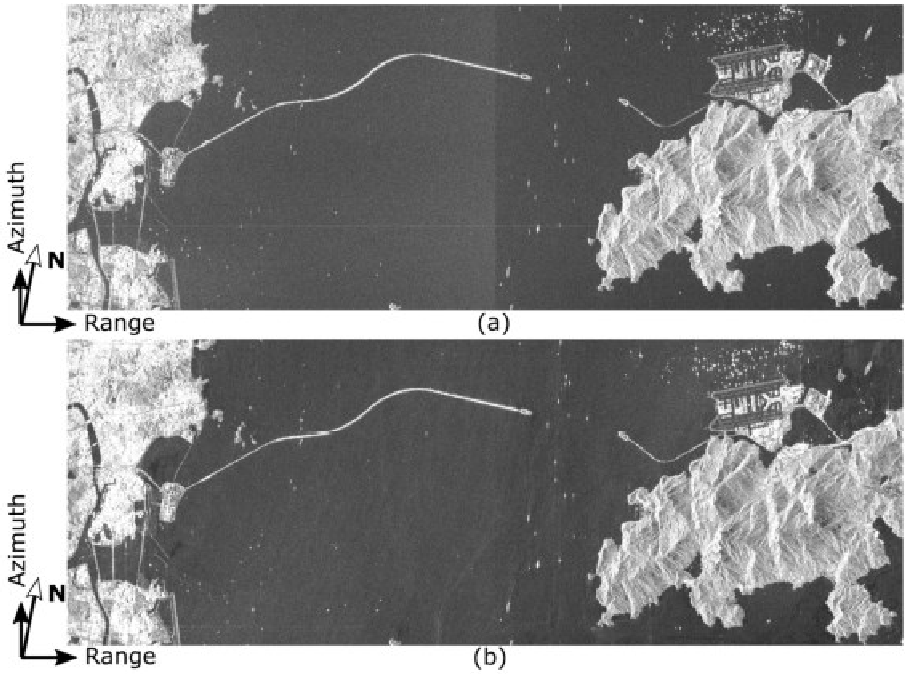


Figure 2.27. Amplitude images acquired in the radar imaging geometry, HZMB, Hong Kong (Xiong et al. 2021).

In Viena, Austria, a comprehensive study performed by Schögl et al. (2021) of the *Seitenhafen* bridge using Sentinel-1 imagery was presented. Atmospheric correction of InSAR measurements using high spatial tropospheric delay maps (GACOS) was also included (Figure 2.28).

Figure 2.28. Analysis of Seitenhafen bridge using space borne data (Schögl et al. 2021).

<u>Ground-Based Synthetic Aperture Radar</u>

Closer to Earth, Terrestrial or ground-based SAR interferometry (GBInSAR or TInSAR) is a remote sensing technique for the displacement monitoring of slopes, rock scarps, volcanoes, landslides, buildings, bridges, etc. This technique is based on the same operational principles of the satellite SAR interferometry, but the synthetic aperture of the radar (SAR) is obtained by an antenna moving on a rail instead of a satellite moving around an orbit. SAR technique allows 2D radar image of the investigated scenario to be achieved, with a high range resolution (along the instrumental line of sight) and cross-range resolution (along the scan direction). Two antennas respectively emit and receive microwave signals and, by calculating the phase difference between two measurements taken in two different times, it is possible to compute the displacement of all the pixels of the SAR image. The accuracy in the displacement measurement is of the same order of magnitude as the EM wavelength and depends also on the specific local and atmospheric conditions. Microwave interferometry systems for remote static and dynamic monitoring are available in the market. For instance, IBIS (Image by Interferometric Survey-Structure), which is developed by IDS and University of Florence, is used on bridges and other structures including buildings, historical monuments and towers. In static, the IBIS-FS is ideal for structure load testing; structure displacement and collapse hazards; cultural heritage preservation. When used for understanding the dynamics of the assets, the IBIS-FS is used for frequency measurements or structural modal shape analysis. Examples of GBInSAR can also be found in the literature.

Erdélyi et al. (2020) presented a spatial data analysis for deformation monitoring of bridge structures. An analysis of the static and dynamic vibrational data using a GB-SAR on the Liberty Bridge (the border between Slovakia and Austria) was developed as seen in Figure 2.29.

Figure 2.29. Analysis of Liberty bridge using Ground-Based data (Erdélyi et al. 2020).

Hu et al. (2019) presented a twofold analysis on a slope and on a bridge. These techniques were applied to monitor the Liusha Peninsula landslide and Baishazhou Yangtze River Bridge. These case studies were measured using a differential GB SAR together with other techniques such as virtual reality-based panoramic technology and ground-based real aperture radar (GB-RAR). Results were presented and compared from both time- and frequency domains (Figure 2.30).

Figure 2.230. Analysis of Baishazhou Yangtze River Bridge using Ground-Based SAR and RAR (Hu et al. 2019).

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. (2020). An IBIS-S sensor was used to study the dynamic behavior of the bridge (Figure 2.31).

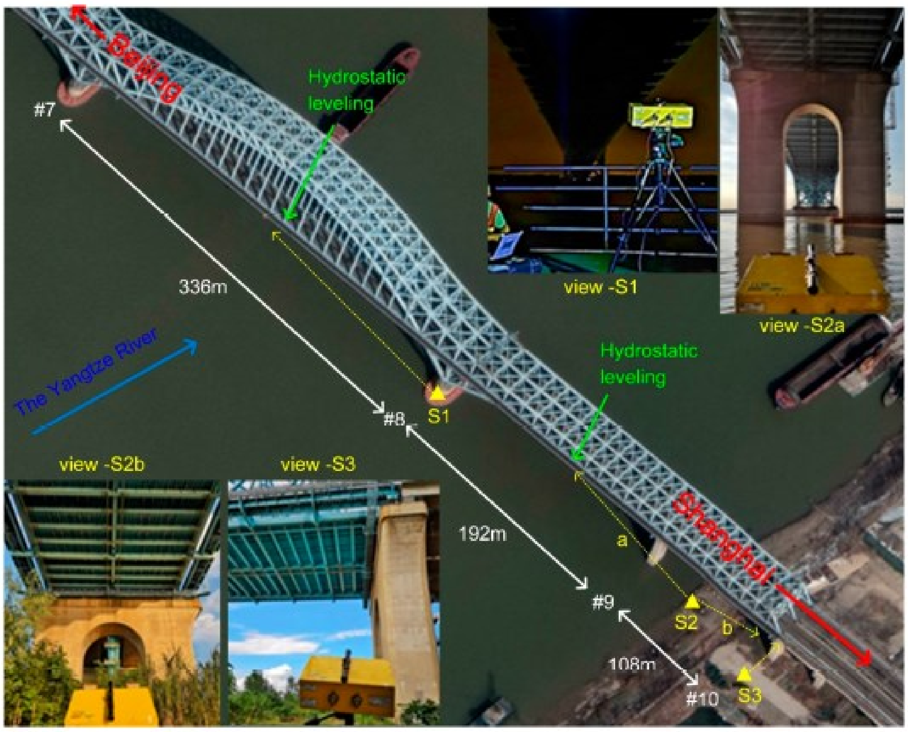


Figure 2.31. Analysis of Nanjing–Dashengguan bridge using Ground-Based data (Huang et al. 2020).

In Italy, Miccinesi et al. (2021) performed a bridge monitoring using a Multi-Monostatic GB SAR. The radar used was a modified version of IBIS-FM MIMO (with four antennae connected). An experimental study of the Varlungo Bridge in Florence was presented as well (Figure 2.32).

Figure 2.32. Experimental setup at the Varlungo Bridge in Florence, Italy (Miccinesi et al. 2021).

In Iran, Pieraccini et al. (2019) performed dynamic studies for masonry bridge monitoring using GB-SAR. The Veresk bridge as well as the Kaflan-Kuh bridge were analyzed. The equipment was a prototype operating in the Ku-Band (Figure 2.31).

Figure 2.31. Analysis of the Kaflan-Kuh bridge, Northern Iran using Ground-Based data (Pieraccini et al. 2019).

Xing et al. (2020) presented comprehensive research on bridge monitoring using GB-SAR. The ground-based radar system was used in Wuhan on a bridge in service crossing the Yangtze River. Improved projection methods for computing the deflection of the bridge were included (Figure 2.32).

Figure 2.32. Analysis of a steel bridge crossing the Yangtze river in Wuhan, China (Xing et al. 2020)

2.3.2.3 Infrared thermometers

The Infrared Thermography (IRT) has been developed to detect existing sub-surface deteriorations including delamination and voids in concrete. As shown in Figure 2.33, 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 the concrete, the delamination can be detected (Hiasa et al. 2018). The IRT camera can also be installed on a vehicle with a normal moving speed to achieve faster inspection compared to other NDT methods (Hiasa et al. 2017). Figure 2.34 shows an example of concrete scanning using 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 of 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. (2021) present an innovative approach based on thermal image analysis to overcome problems related to the image quality. Thirty preliminary tests and three case studies were implemented to show the feasibility of the method. A range of improvement between 8 to 48% was attained that confirms the great potential of thermal images to overcome the limitation of image-based approaches.

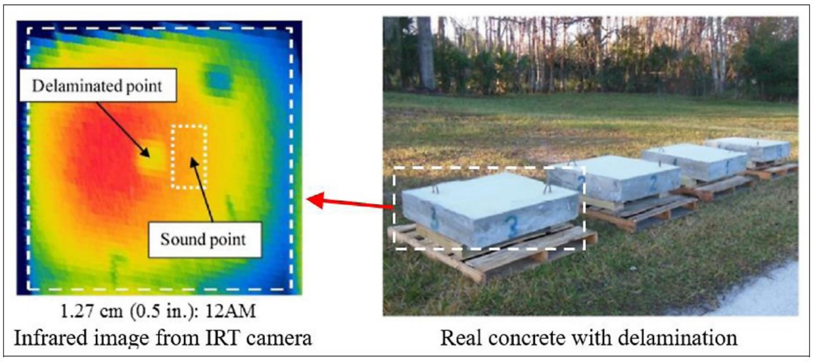


Figure 2.33. Delamination detection using IRT camera (Hiasa et al. 2018).

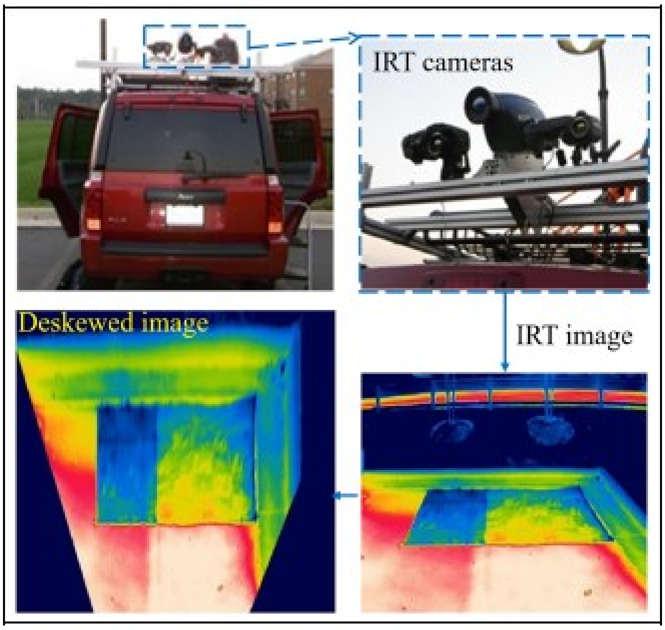


Figure 2.34 IRT camera setup on a vehicle and images from IRT camera (Hiasa et al. 2017).

As shown in Figure 2.35, Matsumoto et al. (2014) presented the time zone when the inspection can be executed. Watase et al. (2015) investigated the favourable time windows for IRT for concrete delamination evaluation by using plates with different thickness and delamination with different depth. The different thickness of plate and the depth of delamination could influence the time window. Hiasa et al. (2017,2018). explored the time window for good inspection of IRT by using experimental and numerical methods and found that optimal conditions for IRT implementation on concrete bridge decks was during night-time under the 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. To segment delamination from IRT images, a proper temperature threshold is necessary as IRT images can also be processed by using similar techniques as for visual images taken by standard cameras. They investigated the temperature threshold using FEM and found that the temperature threshold of delaminated areas of concrete slab with the depths of 1.27 and 2.54 cm defined by FEM simulation could give better prediction performance than directly judging from IRT images with naked eye. 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 of 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.

The visual images from HD camera could assist IRT to discard false-positive prediction of delamination. The image processing approaches in abovementioned applications are general image processing methods such as binarization, morphology, thresholding, gradient analysis, blob analysis, and so on. Besides, the machine learning or deep learning methods can also be applied to process the thermal images. Omar and Nehdi (2017) used an unsupervised learning method, k-means clustering, to segment the mosaicked thermogram of entire bridge deck and identified the objective threshold separately. Based on the different thresholds, the detection of delamination was performed at a higher accuracy. In addition to using a vehicle to do concrete scanning,

Ellenberg et al. (2014) installed IRT cameras and an HD camera on UAV to scan pedestrian bridges. Fig. 2.36 shows hovers and marker. The colour 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.

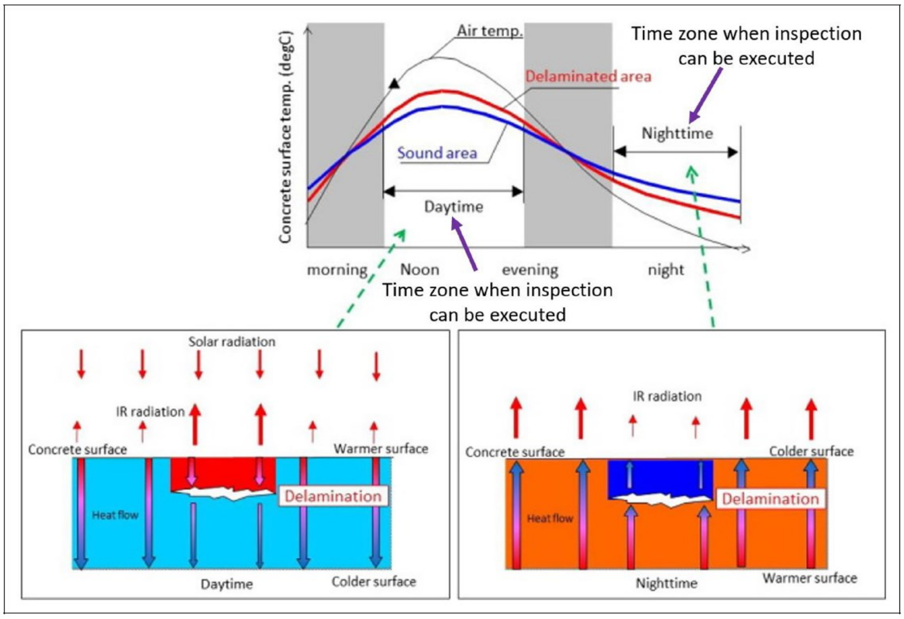


Figure 2.35. Diurnal temperature flow in a concrete structure with delamination (Matsumoto et al. 2014)

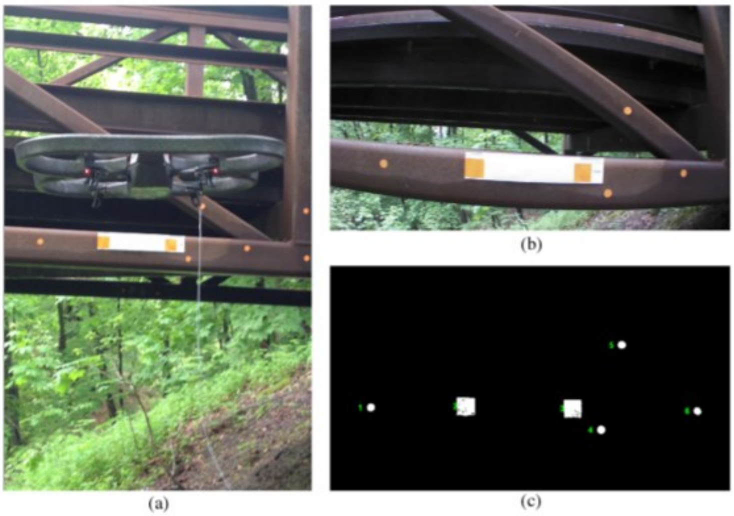


Figure 2.36. (a) Picture of the UAV hovering near the pedestrian bridge; (b) image taken by the UAV showing the markers previously placed; (c) markers identified using the image processing algorithm (Ellenberg et al. 2014)

2.3.2.1 Unmanned Aerial Vehicles

The aerial photogrammetry can be considered as the principal means that the photogrammetry has developed. It was the basic data source for making maps by photogrammetric means. In last years the use of Unmanned Aerial Vehicles (UAVs) has enabled a low-cost alternative to manned aerial photogrammetry. This rapid development can be explained by the spreading of low-cost platform combined with digital cameras and GNSS system, and the rising of digital photogrammetry (Linder, 2016). Today the use of UAV compared with traditional airborne platform decreases the operational costs, reduces the risk of access in harsh environment and still maintains high accuracy potential (Barrile et al. 2019).

Using UAVs and aerial photogrammetry principles is possible to obtain a map, digital model and 3d data of the surveyed area or the object. Currently, analytical tools, such as algorithm for acquisition and software for the generation and manipulation of the photogrammetric data are well developed by scientists. However, these methods are highly empirical and quantitative and qualitative data rely on analysts. Consequentially replication of the existing results can be difficult. For this reason, to ensure data quality and result's accuracy, researchers are focusing on standardization and protocol for information extractions and the integration in a complete process workflow. (Barrile at al. 2019)

3 REQUIREMENTS FOR SHM MEASUREMENTS BASED ON DT

As stated in Boje et al. (2020), “the main challenge on using sensors with DT appears when dealing with the spatio-temporal resolutions, demanding a successful integration of sensors of different capabilities, reading frequencies, accuracies, their respective locations and the inter-dependencies between sensor clusters and networks. The research literature seems to point towards the use of IoT as a means of sensor data capture, almost being taken for granted. However, the delicate intricacies of sensor dynamics for each DT application domain and interoperability with the rest of the DT components remain largely un-explored.” And they add: “BIM lacks semantic completeness in areas such as control systems**, including sensor networks**, social systems, and urban artefacts beyond the scope of buildings, thus requiring a holistic, scalable semantic approach that factors in dynamic data at different levels.”

Therefore, it seems that the interactions between SHM and DT should address both directions, therefore in the following chapters these requirements are analysed.

3.1 DIRECTION 1: WHAT DOES A SHM SYSTEM REQUIRE FROM A DT?

The main requirement from SHM system to DT is the possibility to match structural monitoring system to the digital model and to deploy sensor data visualizations directly onto BIM models, i.e., the possibility for the SHM system to be digitally replicated (Davila et al. 2017). To develop a more detailed requirements, the problem is sub-divided in smaller parts.

BIM lacks semantic completeness in the area of sensor networks and important research effort is necessary into this direction. It is necessary to develop BIM models that allow an effective integration of SHM data with other data sets. Only in this way, the SHM data will be fully implemented in the asset management. The work presented by Davila et al. (2018) is pointing out in this direction. An approach is presented that allows the automatic generation of parametric BIM models of structural monitoring systems, including time-series sensor data, and it enables data-driven and dynamic visualization in an interactive 3D environment.

Existing structures information may not be available in digital form. Twinning (or BIM modelling) is often obtained from CAD models or from point clouds obtained with laser scanning in their As-Built forms. This means that almost every object is approximated in order to transform point-cloud-based descriptors (in non-parametric formats) into parametric primitives. In this sense, it is still difficult or often not feasible to achieve a desired level of geometric approximation for resulting geometrical digital twin. This lack of accuracy in the geometric description can negatively affect the SHM to be efficiently implemented in DT. Therefore, additionally to the possibility of being fully modelled, SHM requires from a DT a geometric-accuracy-based evaluation system for twinning and updating. However, for many assets of the Built Environment, it can be arguably stated that these differences are negligible.

For instance, Lu and Brilakis (2019) explains that the produced geometric digital twins are too ideal to depict the real geometry of bridges. In addition, none of the existing methods for modelling existing structures have explicitly demonstrated how to evaluate the resulting IFC data models in terms of spatial accuracy using quantitative measurements. The method developed by them achieves an average modelling distance of 7.05 cm while the manual method achieves 7.69 cm.

Modern SHM systems can gather huge amounts of data using different sensing techniques, monitoring different parameters (e.g. displacement, acceleration, pressure) and with different formats, which makes difficult the management and processing of data. In addition, regarding the whole life-cycle of the built asset, interoperability problems may arise when combining data acquired in the design, construction and operational phases with different monitoring systems. A DT can manage the data obtained during all those phases and can also improve the SHM by facilitating more intuitive data interpretation, providing a user-friendly interface to communicate with various stakeholders, allowing for the identification of malfunctioning sensors and thus contributing to the self-checking of monitoring system durability

3.2 DIRECTION 2: WHAT A DIGITAL TWIN REQUIRES FROM A SHM SYSTEM?.

Mainly, a DT requires all the processes/tools that allow the appropriate connection between the physical asset and the virtual environment. Monitoring systems allow the time evolution of the physical part. It has been like that for many decades. As a result, it would ideally be replicated/fed in the digital twin. And, therefore, the monitored data should be easily transformed into digital format. As a general idea, the DT requires from the SHM system appropriate, accurate data provided in real-time that can be analysed to inform and predict the behaviour of the built asset, and facilitate decision-making

According to Boje et al. (2020): "*The process of monitoring relies on the sensor network underneath and its ability to select and filter data which is relevant for day-to-day operational management. This data has to be conveyed in a machine interpretable way and subsequently be used for decision making by remote agents (AI or humans) on its virtual counterpart.*"

This main requirement can be split in 3 separate but interconnected phases:

1. First, the SHM system should allow the knowledge of the actual condition state of the real structure via the use of the digital twin.
2. The SHM should provide the data and tools for the prediction of the future condition/response of the real structure by an analysis of the DT response (estimation of future evolution of performance indicators)
3. The SHM should provide the tools for and adaptive response of the structure within the required performance goals based on the calculation of performance indicators obtained through the SHM System.

Some SHM systems will be better suited than others to fulfil such objectives. To get a full digital replica of the built asset at least 3 basic requirements are foreseen:

1. The SHM system should be able to monitor a much area of the physical twin as possible. Redundant information is desirable. This is better achieved by distributed monitoring systems rather than by local sensors. In the absence of a large number of local sensors, the optimum placement of the available ones is of paramount importance regarding the quality and profitability of the gathered data. Available optimum sensor placement methods are summarized in Tan and Zhang (2020).
2. The SHM system should be able not only to detect incorrect performances or damages once they were produced (condition state), but also to monitor the active progression of the damage to forecast future incorrect performance and allow for a proactive and predictive maintenance.
3. As a consequence of the above, in some cases where fast (in time) response is required, the SHM system should be fast in gathering and analysing the data. In this sense, the SHM must guarantee that operational and occupational data could be monitored and analysed in (almost) real-time, providing valuable insights on how the asset is used, currently performing and in future evolving depending on the prospective applied maintenance interventions. Normally, for construction assets and regarding the monitoring of dynamic structural performance, a minimum sampling frequency is around 100 Hz.

It is also required that the **SHM is comprehensive**, in the sense to be able to analyse all aspects that can be due to any malfunction of the asset, independent if during the planning of the monitoring campaign this malfunction was not considered. It means that the analysis of the gathered data by the SHM system should be exhaustive and able to discover any defect even if not thought to be present.

One example that illustrates this problem corresponds to the Interstate-40 Mississippi River bridge in Arkansas. A visual inspection carried out in May 2021, detected the presence of a tie-beam fracture that forced an emergency shutdown of the bridge. Although state officials initially stated that the fracture in one of the 50-year-old bridge's two tied-arch truss navigation spans was not present during its most recent inspection in September 2020, a drone video from May 2019, that was re-visioned after the incident occurred, clearly shows the break already beginning to form (Figure 3.1). According to Arkansas DOT officials, the five-hour drone video was focused solely on assessing the 50-year-old structure's rods and connectors. Although the crack was already present in the video image, nobody took care to check for fatigue cracks in the main members, as this was not the aim of the inspection and the contract.

Figure 3.1: Drone footage from 2019 shows the crack already existed. (Photo courtesy of ARDOT via YouTube)

This example points the fact that SHM is not just deploying sensors accurate enough to record the damage, but also the post-processing techniques should be as automatized as possible to proceed with a full analysis of the recorded data. In this case the automated process of image analysis with the usage of AI techniques would enable prompt detection of crack and would not rely on mere human-centred analysis.

Although strictly dependent on sensing capabilities, the concept of monitoring is achieved at the stage when the influx of sensor data has pre-defined structure and meaning. The SHM system should not only collect data but obtain the data in a pre-defined format. This coincides with the building automation systems (BAS) in the case of the built environment, by which actuations are triggered when certain conditions occur.

More specifically, requirements of different data-gathering techniques, such as sensors, images, and remote sensing devices, under systematic use in several ASHVIN demonstration sites are discussed in Chapter 5.

3.3 SENSORS

From the perspective of the requirements, sensors are classified according to their sample rate. Sensors with high sample rate (>10Hz) are treated differently than sensors with low sample rates (<10Hz). Even though there is not an established border between both categories, it is useful for the consideration of storage and edge computing needs and capacities. Edge computing refers in this context to the computation and analysis of results directly at the node.

- Accelerometers (High sample rate). These devices require high throughput capabilities with a desirable format: JSON. Very often, the acquired data (in the time domain) is bulky and not needed in large volumes. Thus, edge computing capabilities allow filtering data to its minimum expression for efficiency purposes. It is also required to precisely locate these devices at the geometrical model. In the particular case of accelerometers, a relative autonomy to power supply, time synchronization, data storage capacity (locally) and adequate connectivity are desired. When it comes to non-technical requirements, sensitive data handling and encryption is needed (for privacy). Using condition and structural health monitoring data and numerical models, reliability levels will be compared before and after the maintenance intervention. With the condition assessment of the structural health monitoring, from obtained data and numerical models, reliability levels will be compared periodically. Then deterioration and maintenance interventions could be evaluated.

- Environmental magnitudes, inclinometers, transduces, etc (Low sample rate). These devices require low throughput capabilities with a desirable format: JSON. It is also required to precisely locate these devices at the geometrical model. API access to nearby web-based applications is also a very desirable feature.

- Fibre optics. Throughput capabilities ranging from low to ultra-high (when used measuring ultrasonic signals in the range of MHz. It is also required to precisely locate these devices at the geometrical model. Interrogators with open API capabilities and seamless access to the data is of an utmost importance for proper integration.

3.4 IMAGES

From the perspective of the requirements, cameras require precise locations for various purposes. Replicability of image-gathering implies accurate documentation of the spatial location of the camera position together with available photographic metadata. When it comes to non-technical requirements, sensitive data involving human beings imply proper data anonymization (face blurring, car number blurring). Sensitive data handling and encryption is needed. Using condition and structural health monitoring image data on an historical basis implies replicability in time. Then deterioration and maintenance interventions could be evaluated. On the other hand, UAV used for inspection, deliver data on condition of the structures (e.g. cracks, delamination, water leakage, etc.), allowing full reproducibility and traceability of the visual records as well as the corresponding results over time. Replicable flights using drones is feasible yet implies careful control from the user. Therefore it is necessary to use software for flight planning, that will allow to adjust critical imaging parameters, such as camera sensor, flying height, ground speed, forward overlap, side overlap, ground pixel size & imaging frame rate. Flight coordinates (in the form of .srt files) must also be delivered systematically.

3.5 REMOTE SENSING

From the perspective of the requirements, Terrestrial Laser Scanners require extremely high throughput capabilities. Desired formats such as .xyz or .ply are considerably populated with information and thus, require specific treatment if handled in IoT platforms. Replicability issues are also of great concern if successive scans are performed in time. Spatial location and referring of the point clouds is of an utmost importance. A similar treatment of requirements can be established with Ground-based SAR.

When it comes to Satellite geospatial data, it is desirable to access to Copernicus open DIAS platforms via API (onda-dias.eu). Deformations, landslides, water levels, snow quantities or subsidence can be extracted from space-borne imagery. Records of environmental information around the structure to contextualize and enrich other measurements are also needed. This information can be related to vehicles traffic, structural behaviour, and data quality

4 REQUIREMENTS FOR SHM SYSTEMS BASED ON DT

4.1 GENERAL CONCEPTS

The concept of SHM system refers not just to a single technique, but it includes several functions, each of which must be designed carefully. These functions include (1) instrumentation, (2) excitation, (3) data acquisition, (4) signal processing, (5) sensor fault identification, (6) feature extraction, (7) feature processing, (8) damage detection, and (9) alarms and reports.

A typical SHM system contains three main elements: a sensor system, a data processing system (data processing system consists of data acquisition, transmission, aggregation, processing, and storage) and a health evaluation system. Wireless sensor network (WSN) system was studied as data processing system for SHM.

A monitoring system (different from a SHM system) generally contains three components: (1) a measuring device, (2) a method of reading that device, and (3) a method of storing the measurements.

A SHM system able to be used in a DT framework for bridges and buildings with very different characteristics in their dimensions and modal properties requires the system to be **scalable**. This means, allowing the number of sensors to be varied, and reconfigurable, so that the location of the sensors could be changed to adapt the set-up to the structure to be monitored. The system must be also **distributed**, consisting of a set of autonomous modules that must be able to acquire and process data from a set of sensors by exchanging synchronization information with the other modules and with the control module. Other requirements are the ability to acquire the signal from a high number of sensors and to generate proper input signals to command the excitation devices, possibility of acquiring and integrating information from other sensors, both analogue and digital and of autonomous operation with recording in a cloud database.

One important issue when considering the SHM as part of a DT is the autonomy of the systems and the possible ways to obtain energy for their operation (see 4.1.2) and the possibility of real-time damage detection.

Requirements of the SHM system include the need of **data quality** (accuracy and noise reduction and collection of the data in the optimum locations to get the maximum information from the recorded data), **storage capacity** of the SHM data-base system and **robustness/redundancy** of the sensors in the case of long-term monitoring.

Data quality can be affected by **data transferring, data fusion and synchronization** between sensors, data volume, monitoring time, temperature, humidity, and wind, which can explain data variance. According to Davila and Oyedele (2021): "*An essential requirement of the DT paradigm is the synchronization of states between the physical asset and the digital asset. The synchronization entails a two-way data exchange, in which the digital asset obtains data regarding the current and previous states of the physical asset; and, the physical assets get information about how to update its operational parameters.*" Therefore, an important requirement of the monitoring system is the requirement of **full synchronization between physical and**

digital assets. The rate of synchronisation is a very important aspect as real-time data synchronisation is considered to be a must for DTs in Industry 4.0 manufacturing. However, in the built environment, and following the nomenclature by Park et al. (2020), the periodical building and infrastructure inspections appropriate for long-term monitoring could be categorized as “footprint synchronisation”, in which synchronisation is carried out at uniform intervals and all the time-series historical data is aggregated and synchronised. However, for anomaly detection, simulation update and real-time operational optimisations it is more appropriate the “snapshot synchronisation”, in which only data regarding a certain point in time is synchronised on demand.

The SHM must be provided monitoring data in a way that can be integrated within data models that can guarantee **interoperability** among digital systems. Interoperability can be defined as the ability to effectively, accurately, and consistently communicate and exchange information, within different information technology systems. The most widely used data model in the construction sector is the Industry Foundation Classes (IFC). However, IFC does not have yet the capabilities required to fully describe asset operations and to enable asset condition monitoring (Davila et al. 2017).

In addition, as the digital and the physical part of the DT rely on the existence of the sensors, to guarantee the correct communication, there should be some kind of automatic check of the data reliability. This must integrate procedures to automatically detect outliers and how some non-expected data can be interpreted as a malfunction of the monitoring system itself rather than as a malfunction of the physical twin. Therefore**, auto-checking** is another requirement of DT to SHM.

Although different data can have different quality metrics, such as damaged pixels for image data and lost signals for sensor readings, a quantitative assessment can generally include metrics in three aspects, i.e. missing values, erroneous values, and conformance to standards in terms of naming convention, units, and scale. Then, a score can be computed to represent data quality by weighted summing the metrics. Furthermore, to reach a balance between data quality and costs and time to collect data, a quality threshold for different data can be setup so that only data reaching the threshold can be fed into relevant applications. The threshold can be determined based on relative importance of the building, its components, and intended applications.

Examples are already available on the link of DT and SHM for operation and maintenance decision-making. Shim et al. (2019) presented a design concept for a digital twin-based maintenance system for bridges. The method is based on image processing of inspection records. Surface damage detection is automatically performed, and feedback in technical format can be sent to the information system in real time. In Lin et al.(2021), it is shown how with only acceleration and displacement transducers it is possible to build a DT of a long-span cable stayed bridge by carrying out a series of shake table tests in an scale model of the Sutong bridge in China. The DT consists of an updated FE model of the initial drawings. This study suggests that with the advance of FE modelling, structural health monitoring and model updating techniques, the digital twin technology can be used for fragility analysis-based seismic performance assessment of long-span cable-stayed bridges. To accurately assess the seismic collapse of a long-span cable-stayed bridge, the digital twin should be the nonlinearly updated FE model using the latest response data recorded by the sensory system installed on the bridge.

4.1.1 Wireless sensors networks

Sensors network can be wired or wireless. Wireless systems use basically the same measurement devices (or transducers) as wired systems, but they use a transmitter and receiver system instead of lead wires. The key difference is that in wireless sensors network (WSN), sensors work independently while data transferring is based on wireless communication techniques rather than cables. It is recognized that WSN is easier to install and maintain, more stable, and more cost-effective in the long-term (Zhou et al. 2019). Due to their high installation costs, wired sensor networks are generally only feasible for long-term monitoring. WSNs has gained research interest due to its ability to reduce the costs associated with the installation and maintenance of SHM systems. However, in practice, the wired system is still implemented more widely because WSN faces several technical challenges that can affect its reliability and data quality, mainly for long-term SHM, e.g. the lack of power supply, distributed sensors control, and unstable sensor communication (FHWA 2014).

Wireless Sensor Networks (WSNs) consist of small nodes with sensing, computation, and wireless communications capabilities. WSN system is applied in the data processing phase for SHM (Figure 4.1). These sensors can communicate either among each other or directly to an external base-station. These wireless architectures send data of reduced size at specific time intervals (synchronous mode) or asynchronously to specific events. These systems are very versatile and require a synchronization system for the time base to be common to all sensors. According to the communication network type (single-hop and multi-hop), sensor nodes can transmit the measured data either directly or by forwarding data packets of each other to the base station. Base station is a device, which has much higher communication capabilities, more memory, and much higher processing power than the wireless senor node. It usually acts as a gateway to other sensor nodes, which receives and sends data between sensor nodes and remote user.

A diagram showing the process of SHM using WSNs is presented in Figure 4.2.

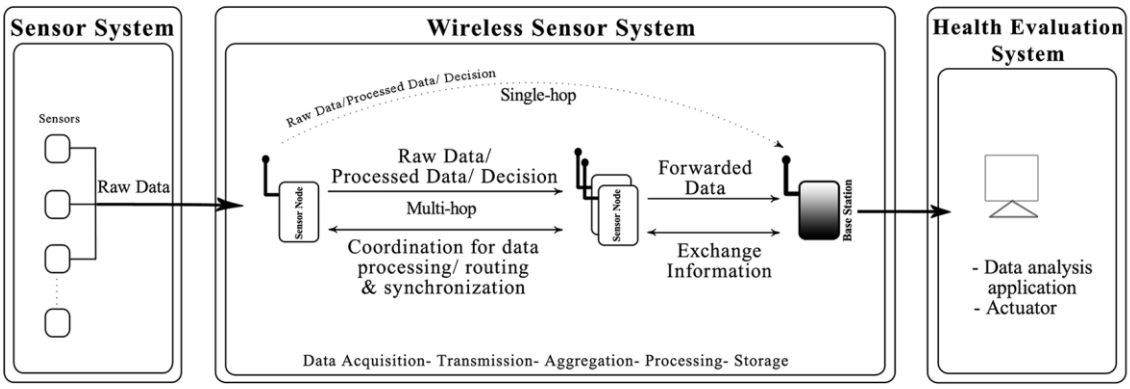


Figure 4.1: Architecture of SHM system using WSN (Abdulkarem et al. 2020)

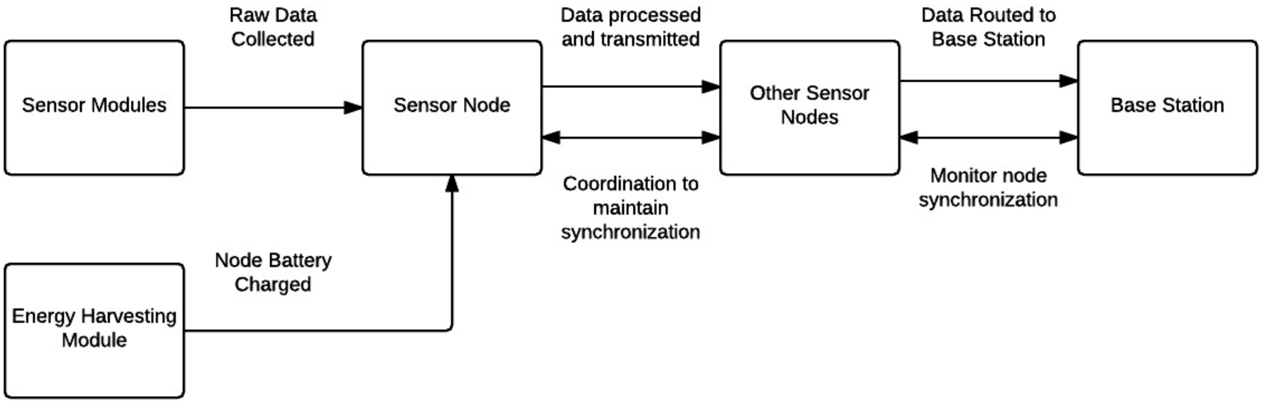


Figure 4.2: SHM using WSNs (Noel et al. 2017)

WSN refers to a collection of distributed and dedicated sensors for monitoring and recording conditions of environments, equipment, structural response. The sensors in WSNs are called nodes and they measure environmental conditions such as indoor temperature and relative air humidity, structural conditions such as acceleration, strain, displacement, etc. This raw data is processed to extract features for performance monitoring. The typical architecture of a sensor node is shown in Figure 4.3.

The main issues when deploying WSN for SHM are the **time delay, scalability, synchronization, and energy consumption.**

Time delay requirements depend on the type of SHM implemented. In the case of long-term monitoring the requirement is not so strict. In fact, a time delay of, for instance, 10 hours to collect, process and aggregate data at the base station can be acceptable as long as data transmission is reliable. However, this is a real issue when the SHM is intended to monitor a sudden event hampering the structure, as an earthquake or other natural disaster.

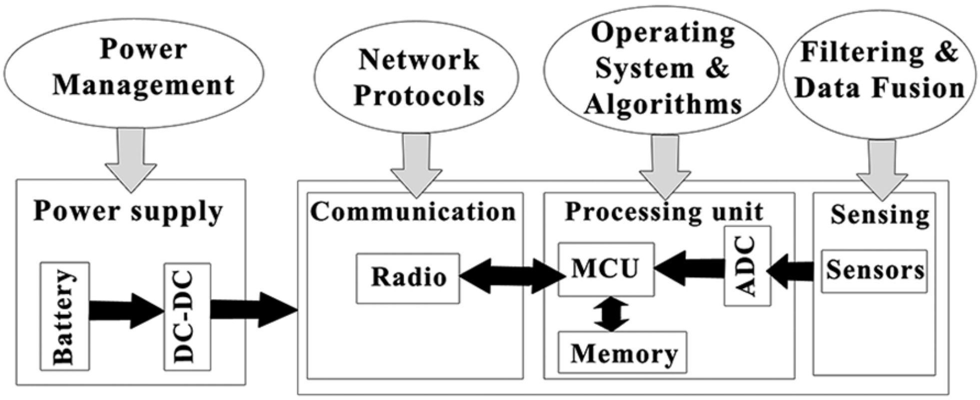


Figure 4.3: Sensor node block diagram ((Abdulkarem et al. 2020)

Scalability is a network's ability to grow in size while continuing to provide a quality of service that meets application requirements with an acceptable complexity. Ensuring scalability is particularly challenging in WSNs for SHM due to the huge quantity of data collection and transmission required. Scalability depends on several factors: data transmission rate, data storage availability, power consumption, time-synchronization error, and processing algorithms. In general, a network can successfully scale as long as the maximum network node time-synchronization remains below 120 microseconds.

The requirement of scalability for a monitoring system can be better achieved by WSNs. Wireless sensor networks allow for a distributed processing instead of a centralized processing normally used with wire-based systems. As presented in figure 4.4, in WSN data processing can be done in 3 different ways: centralized, local or cluster-based. The selection of the processing method is mainly based on the type of damage detection technique used for the structure. However, other factors should be also considered. For instance,. centralized processing is the data processing technique typically used in WSNs for SHM. If delay is an issue, centralized processing should be avoided. An advantage of local processing over cluster-based processing is that it improves network robustness (the failure of a sensor node does not mean the failure of the complete network). In clustering, sensors nodes are grouped into clusters and each cluster has a node designated as the cluster-head (CH). In a given cluster, all nodes, except for the CH, can only communicate with the CH. The CH can communicate with all nodes in its cluster and nearby CHs. Clustering improves scalability, simplifies routing, and extends the network lifespan. In general, the primary goal of using cluster-based processing is to reduce the overall network energy consumption and improve the scalability.

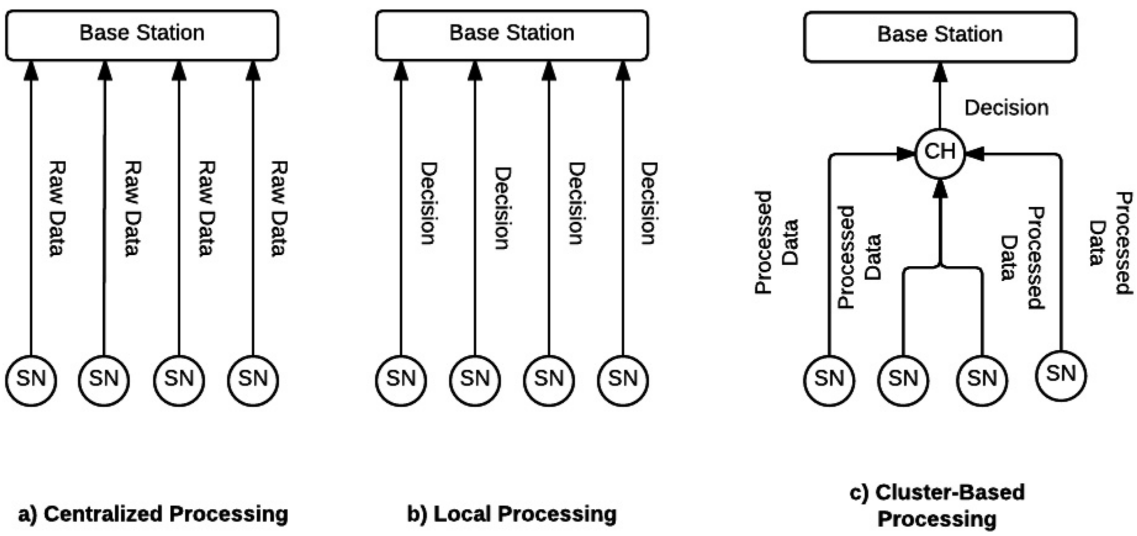


Figure 4.4: Network Data processing types (Noel et al. 2017)

In addition to the sensor nodes, WSNs consist of gateway nodes that act as the bridge between the local sensors and the remote applications such as cloud hosted databases and online web pages that visualize data. In recent years, WSNs gained attention due to the emergence of IoT and proliferation in MEMS technologies. **Synchronizing and transmitting** massive amount of data in WSNs are considered to be a real challenge due to limitation of battery and data rate related to sensor node. Time synchronization between the sensor nodes is crucially important for accurate vibration-based damage identifications. It is more or less accepted that the maximum node time synchronization error must be below 120 μs. WSNs for SHM have similar quality of service requirements to normal WSNs except that network time synchronization errors must be minimized. Time synchronization error depends on clock synchronization errors, non-simultaneity in sensor start-up, differences in sampling frequency and non-uniform sampling intervals.

The practice of performing SHM algorithms directly on the sensor node can be used to save considerable energy within WSN by taking the advantage of inherent local processing that is performed within the embedded microprocessor of the sensor node. Transmitting data requires more **energy consumption** than processing data. To reduce network data traffic and energy consumption, it is important to consider challenges associated with employing distributed data processing in WSN in conjunction with requirements of SHM algorithms. Data transmitting and energy consumption can be highly minimized by performing the data processing in the sensor node. Energy efficiency is reduced by high volume of data collected and transmitted. Significant data reduction can be achieved by distributing processing throughout the network as opposed to centralizing processing at the base station. Another way of energy saving is the so-called event-based wakeup scheme or time-triggered sampling mode. The sensors are normally maintained in the sleep mode, and they start measuring when the signal level reaches some targeted threshold (as an example, sensor node only wake-up when the moving average of the vibration signal exceeds a pre-defined wake-up threshold). However, one of the challenges of purely event-based wakeup schemes is ensuring synchronicity between sensor nodes. Finally, energy harvesting techniques (4.1.2) have the potential to greatly improve WSNs lifespan. To date only a small number of WSNs for SHM have employed energy harvesting systems to extend network lifespan and optimize network design.

A comprehensive review of academic wireless prototypes and commercial wireless platforms used for SHM is available in Abdulkarem et al. (2020). MEMS sensor node is called mote, which can be considered the most popular commercialized platform. There are several alternative low-cost platforms that are used for SHM application instead of existing commercial wireless platforms. For instance, Arduino is an open-source microcomputer platform that provides several board variants.

A practical example of a wireless smart sensor network for vibration-based structural health monitoring can be found in Navabian et al. (2020)

The sampling rates normally required for successful SHM (around 100 Hz), increases the amount of collected data and, consequently, the amount of data aggregated, processed and transmitted in the overall network, that may be taken into account when designing a WSN.

4.1.2 Energy harvesting

In the same way that sensor data can be transmitted wirelessly, it is also interesting to get energy for the SHM system without the need to use direct connection to power grid or batteries. This becomes more important when the sensors are located in remote locations or in places with difficult access. The ability to power the sensor nodes without wires or periodic battery replacement would allow for fully independent, long-term sensor nodes. The idea is to get energy from the close environment. In Weaver (2011), an extensive literature review on energy harvesting is presented, followed by approximate power requirements for an example Wireless Sensor Node. In the case of bridges, it also examines the availability of in situ energy on and around a highway and the estimation of theoretical power available from each source. One possibility for bridges and buildings is the use of the self-vibration due to the operational loads to create energy using piezoelectric materials.

4.1.3 Data storage

Image and sensor data needs to be transferred to and hosted in an operational database on a server. This can be a physical server on site or a cloud-hosted server. The server specifications and data storage requirements need to be assessed with reference to the estimated expected data volumes. In this sense, requirements for data storage from a DT approach has two main aspects:

1. **Historic data**: Where the DT is required to provide a damage detection and prognosis of future performance, first the un-damaged state of the physical asset performing in a correct way should be appraised. In some cases, this can require a large volume of data, mainly when the identified damage features are sensible to environmental conditions (temperature, humidity). This requires the collection and storage of data involving long periods of time, at a minimum one year to reflect all possible environmental scenarios.

For a single sensor channel, Table 4.1, taken from CIRIA report shows approximate typical data volumes which could be expected at different sample rates. These are the volumes required for data that is present in an operational database on a server.

Table 4.1: Typical volumes of data from a sensor (from CIRIA 2020)

Sample rate	Rate per day	Date per month	Date per year
1 reading per hour	7 kB	0.21 MB	2.6 MB
1 Hz	25 MB	0.75 GB	9 GB
10 Hz	253 MB	7.5 GB	90.2 GB
100 Hz	2.47 GB	75.2 GB	902 GB

Based on current technology, an example large SHM system with a high proportion of dynamic sensors (sensor channels with data saved at 100Hz for some of the time, related to specific high wind or traffic events), would be estimated to produce an annual volume of data in the range 36TB to 600TB, depending on how much dynamic data is stored (CIRIA 2020).

2. **Real-time data**: As the DT should react in real-time to the changing conditions of the physical asset, the huge amount of data must be also processed in real-time, what derives on low amounts of data to be stored. Once the data is gathered, processed and transferred to the digital twin, this data can be already abandoned or archived and the storage capacity provided for a new set of fresh data.

Different data types need different formats. Most formats (e.g. .csv and .pdf) are common and traditional formats, while new formats, such as .hdf5 and .ifc, are being increasingly adopted. The former is good at handling massive SHM data. The latter can encode geometric (e.g. geometry of components and damages) as well as some semantic data (e.g. condition indexes) in BIM (Huthwohl et al. 2018).

4.1.4 Interoperability between different SHM systems

With the increasing diversity of data types, a standard and software neutral schema is necessary to integrate and share data efficiently. Thus, Industry Foundation Classes (IFC), which is based on EXPRESS and STEP language and is originally designed for buildings, has been borrowed in the bridge sector. Continuous efforts are made to extend IFC for bridge projects (Huthwohl et al.2018, Zhang et al. 2016). Huthwohl et al. showed how in three steps, IFC in its latest version provides sufficient functionality to serve as a basis for integrating relevant defect information and imagery coming from standard bridge inspections. This is achieved by standardizing type defects and properties from existing bridge inspections manuals from different countries, modelling these defects entities as objects, modelling their properties and their relationships, and mapping to appropriate existing IFC entities.

The latest IFC schema can encode various data for bridge O&M (e.g. alignments, geometry and structure conditions) and can be converted to XML (i.e. ifcXML). However, Transportation Agencies can take different approaches to organize bridge components. The bridge can be divided into components (e.g. girder and deck) or into finite elements (Masahiro and Takashi, 2013). These requirements can affect the way that inspection data are recorded. Thus, it is crucial to ensure that data schema matches the monitoring and inspection procedures to smoothly integrate the data into the database.

Although studies are beginning to apply .ifc format and extend schemas (e.g. XML and IFC) for bridge operation and management, they mainly encode geometry and structured data and only recently begin to cover semantic and unstructured data (e.g. inspection results). However, many data types are not covered, especially those that are usually not included in digital models (e.g. environment and traffic data in bridges) or those that are difficult to represent by a structured format (e.g. topology of bridges). Such data can be critical for maintenance applications. Hence, the lack of neutral formats and schemas can hinder these applications if needed data are not integrated to enable relevant functions.

Davila et al. (2017) discusses the issue of integration of sensor data into BIM. The paper explains the modelling of structural performance monitoring systems in a Building Information Modelling (BIM) environment and how this permits sensor data to be visualized directly on BIM models. It is concluded that the data model standards are not yet sufficient to describe monitoring systems and processes, and there are no formalized directives or standards to manage and visualize sensor data in a BIM environment. The case study shown in the paper explains how to facilitate more streamlined approaches to structural monitoring and data management and allow for a quick interpretation of general trends in structural behavior.

4.1.5 Systems for operational monitoring in buildings

In residential and industrial buildings, apart from the need of a correct structural health monitoring, it is also of importance the monitoring of the correct functional performance to provide correct live standards to their residents and users. Sensing technologies are essential to data-driven O&M of buildings. In buildings, data is available on:

1. Computerized Maintenance Management Systems (CMMS) which are intended to handle emergency work-orders and occupant service requests. They include frequency of thermal complaints, HVAC frequency failure among others

2. Building Automation Systems (BAS): temperature, humidity, CO2, airflow, occupancy sensors, valves, dampers

3. Lighting control systems: can be used for energy efficiency analysis and improvements

4. Metering: the meter data types can include utility meters (e.g., electricity, natural gas, water) and sub-meters for end-uses (e.g., lighting, plug loads, heating, cooling).

5. Access control and security camera networks. These networks in office buildings can monitor the entry/exit events at the doors, stairwells, and elevators, and in turn, can help characterize the occupancy patterns. For example, the occupancy count can be estimated from access cards such as RFID (Radio Frequency Identification) tags and magnetic stripe cards. Security camera networks are increasingly designed with built-in computer vision capabilities – which are primarily intended for intrusion detection. However, these security cameras can also be used as computer vision-based image processing sensors to estimate the building or floor level occupancy counts.

6. IT networks also provide insights into building occupancy patterns. The Internet of Things (IoT) systems such as networks of mobile devices and wearables are also emerging data sources to monitor thermal comfort, indoor air quality, and occupancy patterns.

7. Human Resources (HR) databases can provide insights into occupant comfort, satisfaction, and productivity. For example, metrics inherent in HR databases such as sick days, absenteeism, and employee performance assessments can be analyzed in tandem with indoor environmental quality indicators.

In this context, a monitoring framework based on BIM and IoT was implemented by Kang et al. (2018), providing a comprehensive view of the buildings' state and improved information utilization efficiency. Fargnoli, et al. (2019) integrated BIM-based approaches in a Product-Service System context to improve the management of building equipment O&M, and they implemented the framework for elevators of an existing building.

4.2 NON-CONFORMANT PERFORMANCE: DAMAGE DETECTION

Damage and abnormal performance detection are the objectives of a SHM system. In the case of a physics (model)-based approach for the digital twin, it is necessary that the geometry of the asset and the deployment location of the sensors are known with a high accuracy. Otherwise, the comparison of the response of the virtual and physic twin will not be accurate enough and this can derive on wrong decision-making. In the case of data-driven models this requirement is not so important as the damage detection method does not need to consider a physic-based model.

Classification for damage identification techniques distinguishes between methods used for continuous monitoring of structural performance and methods applicable to the detection of damage, caused by extreme events. For example, a system that uses continuous or periodical accelerometer measurements from sensors located permanently to a bridge is different in terms of instrumentation and data acquisition requirements from a system that does not acquire data except during and immediately following an earthquake or a hurricane. It should be noted that the primary distinction between these situations are the sensors and data acquisition system requirements. However, the same kind of analytical techniques can be applied to the data to determine the integrity of the structure

4.2.1 SHM systems for crack detection

Electrical properties of cementitious materials can be used to detect and locate defects such as cracks in concrete.

Options for direct sensing of crack damage include piezoelectric and acoustic techniques that are based on the analysis of wave propagation in the structure. By using active sensors (that serve as wave emitters and receivers) and by performing the appropriate analysis, it is possible to detect and localize cracks

Yao et al. (2014) summarize the knowledge about cracking in concrete and steel and its sources, review both existing and emerging methods for crack detection and characterization, and identify the advantages and challenges for these methods. Two sensing approaches (direct and indirect) and two data analysis approaches (model-based and model-free or data-driven) are identified to envelop all existing technologies for crack detection. In direct sensing, the crack is detected and localized directly as an unusual change in the output from the sensors affected by the crack. Typical examples of technologies that enable direct sensing include discrete strain sensors (electrical or fiber optic, short gage, or long-gage), distributed strain sensors (electrical or fiber optic), wave monitoring sensors (acoustic emission and wave propagation sensors), and eddy current sensors. Discrete sensors (electric or fiber optic, short-gage, or long-gage) that are sparsely spaced in real structures may suffer from insufficient spatial coverage. This can be solved by using distributed optical fiber sensors (DOFS).

Indirect sensing methods are based on measurements made by sensors that are not necessarily in direct contact with damage (e.g., accelerometers, strain sensors that are not at the location of the damage, remote sensors, etc.). As opposed to direct sensing where the damage is detected directly as a noticeable change in output signals of affected sensors, in the case of indirect sensing, the sensors usually do not manifest noticeable changes in output signals. Consequently, the recorded data must be analyzed using various classes of sophisticated algorithms in order to ascertain crack detection and perform crack characterization by data mining. Two approaches in data analysis are identified: model-based and model-free (data-driven). The main challenges for the application of model-free approaches are related to its sensitivity to noise generated by loading or environmental variations and the lack of supervised training for algorithms. Both challenges can lead to false positive and negative detections of cracks, which reduces the reliability of such methods in real-life settings.

For instance, in bridges, various methods have been applied to identify existence and location of damages objectively and accurately, including statistical approaches, e.g.

regression, hypothesis testing, and regularization (Pan and Yu 2019), and supervised ML models, e.g. SVM, and ANN (Pan et al. 2018). Unsupervised ML, e.g. k-means clustering, can also be applied to detect damages or categorize damages so that the thresholds are determined more objectively (Omar et al. 2018). In some cases, control charts are used to facilitate data analysis by enhanced visualization of the mean, upper, and lower limits of responses (Chen and Durango-Cohen 2015).

4.2.2 Damage and non-conformant performance detection in buildings

In buildings, the detection of anomalies (malfunctions) for asset monitoring is challenging and problematic due to the high degree of system complexity and large scale and the number of components in this highly integrated system. Various tools and systems have been developed to improve O&M management, such as Computerized Maintenance Management Systems (CMMS), Computer-Aided Facility Management (CAFM) systems, Building Automation Systems (BAS), and Integrated Workplace Management Systems (IWMS) (Sapp 2015). But it still requires significant effort and time for facilities management (FM) professionals to extract the diverse O&M information they need (e.g., data within CMMS, specifications, 3D models). CMMS, IT network, access and security control, and HR databases can provide insights into traditionally unmeasured quantities regarding occupancy, occupant behaviour, perceived comfort, satisfaction, and productivity. However, there is still a lack of an integrated platform that could manage information distributed in different databases and support various activities in O&M phases.

IFC is not well suited for asset condition monitoring in the built environment. For this reason, Lu et al. (2020b) presents a DT-based anomaly detection system and an appropriate method of data integration based on the extension of IFC. A case study is presented related to centrifugal pumps in the heating, ventilation, and air-cooling (HVAC) system. The proposed DT-based anomaly detection methodology can carry out a continuous anomaly detection of pumps.

Non-conformant performance is checked when change points are detected where the generative parameters of the building operational data sequence drift. Combined with the external building operation information, real anomalies that result from asset failures could be filtered as the trigger for following-up early warnings. Generally, the anomaly detection of asset monitoring for O&M management requires cross-referencing of multiple data sources for building facilities information. A comprehensive solution is necessary for streamlining anomaly detection, in which data interoperability and reusability need to be significantly enhanced. Digital Twins (DTs) are considered to be such a comprehensive solution.

For **point anomaly detection**, the so-called normal operation conditions (baseline) must be defined based on either historical operation data or simulation models, which serve as baselines and are thereafter compared with current behaviour to detect anomalies. Typically, process history-based methods are extensively adopted because they depend on the past building operational data without requiring any physical interpretation of the systems. Moreover, their data-driven nature makes these methods extremely easy and inexpensive to implement, as long as data satisfying quality requirements are available.

Change point detection is a form of contextual anomaly detection, which looks for abrupt variations or change points in the generative parameters of the building operational data sequence. More precisely, the found change points could be suspicious candidates for anomalies but not necessarily need to be an anomaly, serving as an early warning symptom for the problem within the underlying building system. Cross-referenced external contextual information must be integrated to help determine whether the detected change point attributes to the normal condition variations or emerging anomalies. However, the workflow and information exchange behind the cross-referencing process is very complex. Fortunately, DT of buildings is a solution that integrates multiple fragmented data sources and thus greatly enhances the data availability for buildings (Gunay et al. 2019). With the help of the DT model, normal operating condition changes could be excluded, leaving only the suspicious anomalies that help facility managers identify the problems as early as possible.

Effective data integration through information sharing is a critical factor in achieving effective anomaly detection, especially for excluding change points caused by normal operating condition changes, to avoid any false alarms. The fragmented nature of building data sources presents a challenge in developing a valid anomaly detection strategy.

The O&M data is usually saved in different formats. It thus requires great efforts and time for FM staff to extract the diverse and scattered O&M information required. A unified and standardized data schema is needed for information integration and achieving smart asset management in the O&M phase. Because of the flexibility and consistency of IFC schema in the building lifecycle, IFC schema is the most suitable and fundamental data schema for wider BIM implementation and information integration

4.2.3 Vibration-based damage detection

Avci et al. (2021) present a complete review of vibration-based damage detection techniques in built assets. Their main contribution is the description about the transition from traditional methods to Machine Learning and Deep Learning methods. Some of the main conclusions obtained from the analyzed techniques are as follows:

1.- Machine learning techniques are based on feature extraction and feature classification. For this reason, the ML-based methods are more generic and advantageous than non-ML based methods in vibration-based structural damage detection in civil structures.

2.- Modal parameters (frequencies, mode shapes and damping) are not recommended as damage-sensitive features in ML-based methods as they are low sensitive to certain types of structural damage and because of their sensitivity to environmental and operational effects.

3.- Convolutional Neural Networks (CNN) are able to detect and locate damage directly through the raw acceleration time-histories without any need for data preprocessing or hand-crafted feature extraction.

Because ambient excitation is always present, the techniques used for identification of modal parameters only based on structural responses (OMA: Operational Modal

Analysis) can be applied to continuously process time series acquired by a permanent installation of a set of accelerometers. The processing of data collected by dynamic monitoring systems with the aim of identifying structural deficiencies comprehends not only the identification of modal parameters but also removal of the environmental and operational effects on natural frequencies and mode shapes

Damage detection based on Machine-learning techniques does not conflict with model-based methodology. The output of ML can be incorporated into the structural analysis model and improve the accuracy of the model-based approach. The final goal of ML is to achieve unsupervised damage detection with self-learning ability.

In the last years, there has been significant research which shows that data measured on a passing vehicle contains valuable information about the bridge condition. These methods are so-called **"Drive-by" bridge monitoring** in which sensors are installed on vehicles and used to infer information about the condition of a bridge as they pass over it (Malekjafarian et al. 2015). Mei et al. (2019) proposed an indirect damage detection method based on mel frequency cepstral coefficients to detect multiple damage states on a lab-scale bridge-vehicle model. They showed that the damage in the bridge model could be identified using the sensors deployed on a car model even if the speed, weight, and suspension of the car were varied between experiments.

Hester and González (2017) discuss the merits and limitations of using drive-by monitoring to detect localized damage in a bridge. Yang et al. (2020) present a comprehensive review of the different vehicle-based methods for damage detection in bridges, jointly with their main advantages and disadvantages and applications of the techniques to highway bridges and railway tracks.

4.3 PREDICTION OF FUTURE PERFORMANCE

A successful damage prediction model would require the assessment of the structure's current health, a forecast of the structure's load, and a computational tool able to describe the behavior of the given structure. The computational tool can be either model-based or data-driven based. In any case, predictive loading model (including environmental effects) requires additional sensors to describe loads and, consequently, additional data collection, aggregation, and processing requirements. The predictive model itself would further increase networking and data processing, which may be challenging for WSNs due to the huge increase on the amount of data to deal with.

4.3.1 Model-based

Finite Element (FE) models are the most common approach to embed data and mechanical models into software, which automates computation while simulate and visualize damages, modal properties, and deterioration processes and can model the future performance of the construction. FE models are usually created according to structure´s profile data, e.g. drawings and 3D models. However, initial FE models have discrepancies with reality. Therefore, they should be updated before being used for FE analysis, using actual SHM data or structure´s profile collected by NDTs (e.g. LiDAR and LDV). (Dai et al. 2014). The updating process can be improved by sensitivity analysis and optimizing algorithms, e.g. GA, which can find optimal parameters that minimize the difference between reality and FE models.

4.3.2 Data-driven based

The work by Tibaduiza-Burgos et al. (2020) presents a review of data-driven algorithms for damage identification in structural health-monitoring applications. The review covers damage detection, localization, classification, extension, and prognosis. It also includes information on the types of sensors used as well as on the development of data-driven algorithms for damage identification.

5 CASE STUDIES: DEMONSTRATION PROJECTS FOR BRIDGES AND BUILDINGS

5.1 DESCRIPTION OF CASE STUDIES

5.1.1 DEMO#1: BRIDGES IN HIGH SPEED RAILWAYS NETWORKS.

Alta Velocidad Española (AVE) is a service of high-speed rail in Spain operated by Renfe, the Spanish national railway company, at speeds of up to 310 km/h (193 mph). AVE trains run on a network of high-speed rail tracks owned and managed by ADIF (Administrador de Infraestructuras Ferroviarias). The first line was opened in 1992, connecting the cities of Madrid, Córdoba and Seville. Unlike the rest of the Iberian broad gauge network, the AVE uses standard gauge. This permits direct connections to outside Spain through the link to the French network at the Perthus Tunnel. AVE trains are operated by RENFE, but private companies may be able to operate trains in the future using other brands, in accordance with European Union legislation. Alta Velocidad Española translates to "Spanish High Speed", but the acronym also stands for the word “ave”, meaning "bird". Figure 5.1 displays the network at February 2021 in which “in service”, “under construction”, “projected” and “in partial service” branches are highlighted.

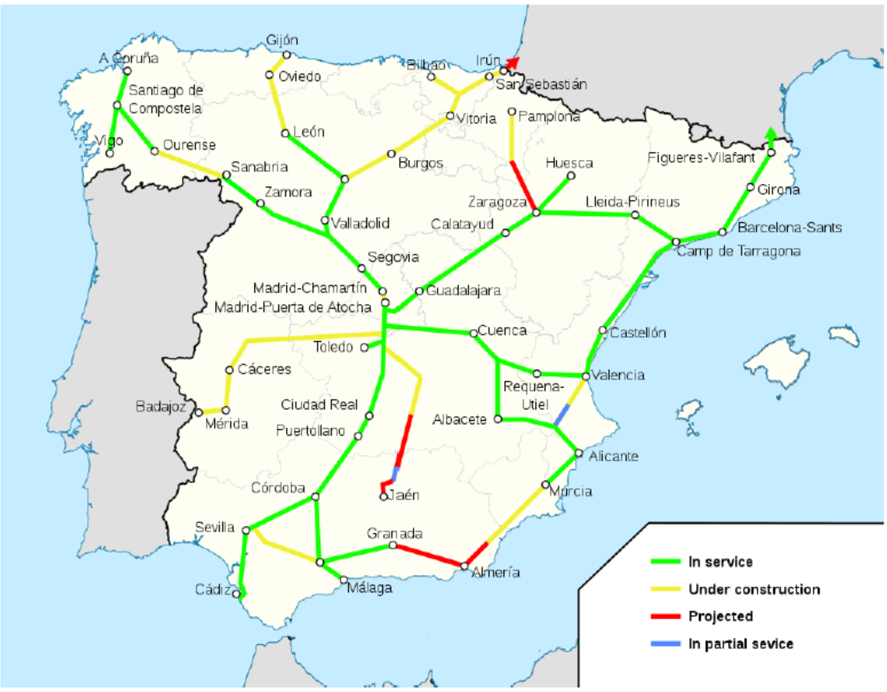


Figure 5.1: High Speed Railway Network. Spain. February 2021. Source Wikipedia

The branch of the Highspeed Railway; Madrid-Bajadoz has been under construction in recent years. It is supposed to connect in the years to come two major European cities in nearly 3 hours by train: Lisbon and Madrid. The map provided in Figure 5.1 shows its specific location. Its origin is some 50 kilometres South of Madrid and then the line goes South-West direction towards Badajoz. Presently, it has been built only on the Spanish side. The length of the double line from Madrid to Badajoz is 437 kilometres and it includes several viaducts, bridges, and tunnels. European funds (FEDER) under the challenge of sustainable transportation helped develop this strategic infrastructure. Figure 5.1 displays a schematic overview of the major stations connected by the line.

The branch of the Highspeed Railway; Plasencia-Bajadoz is expected to open in the years to come. Presently, works on the mechanics, electrics, services, and other necessary infrastructure are being finished. The railways as well as major infrastructure are being tested and monitored. The Spanish design and engineering firm GEOCISA, which is a collaborator in ASHVIN, is currently performing systematic load tests on the bridges belonging to this branch. The company has access to load tests of more than 15 bridges of different sizes. The bridges vary in type from simple underpasses to complex arch bridges, including a top-5 world record defined by a concrete arch (Almonte Viaduct). Geocisa has provided access to the documentation of those assets.

These routine load tests are meant to verify standards on the design and construction of the bridges. Load tests consist of the development of a structural model representing a realistic load that is put on the bridge. Measurements related to the response of the structure when subjected to those loads are taken and compared. If results are within tolerances, the bridge is considered as acceptable for operational stage.

The load tests represent an ideal milestone for twinning bridges. On the one hand, specific, bespoke structural models are performed. On the other hand, measurements quantifying the structural response are taken. If both results are matched using not only basic comparisons but comprehensive digital twinning, the asset enters the service phase not only physically, but also virtually. The demonstrator #1 is aimed at establishing requirements, procedures and for the generation of the most realistic virtual replica of the physical bridges that can be used during operation. Presently, current numerical methods focus primarily on the virtual reproduction of the assets. Models are generally calibrated with existing laboratory or real tests. The twinning of these bridges also includes the integration of data from sensors for model updating or hybrid simulations within the realm of such simulations. A close inspection of the pool of bridges has already been given. Together with Geocisa, documentation of all assets has been studied. Among all bridges, three assets have been selected for implementation of the ASHVIN set of measurements, from which two are shown in Figure 5.2. In Table 5.1 the overview of implemented SHM systems for Demo#1 are presented, which are integrated into ASHVIN DT platform.

Figure 5.2: Valdelinares Viaduct (left) and La Plata Viaduct (right)

Table 5.1: Planned measurements for demonstration site #1.

Type of data	Device/sensor	Rate	Volume	Data format	Data collecting[1]	Storing of data
Deflection at midspan and displacement of supports	LVDT +- 5 mm	100-to-200 samples per second	2-3 Hours of continuous measurement	Txt	Data from sensors is sent using a HBM MGCPlus data logger.	Locally and then sent to the Mainflux platform.
Inclination	WitMotion WT901B TTL	100-to-200 samples per second	2-3 Hours of continuous measurement	JSON	Data is directly sent to Mainflux using a MQQT	Directly to Mainflux Format
Acceleration	BeanAir (MQQT Protocol). ADX345 + ESP32. Netplus	100-to-200 samples per second	2-3 Hours of continuous measurement	.txt	Data is directly sent to Mainflux using a MQQT	Directly to Mainflux Format
Environmental conditions (Temperature and Humidity)	DHT22	1 samples per minute	2-3 Days of continuous measurement	JSON	Data is directly sent to Mainflux using a MQQT	Directly to Mainflux Format
Deflections (remote sensing)	Interferometer	200 samples per second	Episodic	Point Cloud	A radar interferometer is owned by the company GEOZONE which collaborates with Geocisa.	Locally, treated and subsequently sent to Mainflux

5.1.2 DEMO#2: RESIDENTIAL BUILDING IN POLAND

This demonstration building is a typical example of the residential building that needs intermediate renovation activities. This two-storey building was constructed in 1921, it has 7 flats and 16 building occupants, it is located in Gdynia in Poland. It is a public building that has a function of social housing. The building is owned by the City of Gdynia, the unit that is responsible for the building management is the **Municipal Buildings and Housing Administration of Gdynia.** The living area is 260m2 and the heat is generated by the tiled stoves (for coal and wood). The building envelope is not insulated. The building has very low energy performance estimated as 689 kWh/m^2 year, see Figure.

Figure 5.3 Gdynia. Residential Building

Building refurbishment aims to protect the building from heat loss and to drastically reduce the energy consumption needed to heat the building and to heat the water. In the vast majority of cases, excessive heat loss is one of the reasons for the high operating costs of buildings. These are the result of poor insulation of external walls, leaky windows and insufficiently efficient heating systems. That is why many buildings need to be renovated (in some cases need to undergo the deep renovation). Renovation activities contribute to reduction of the energy demand of a building. Building refurbishment concerns already existing buildings, which due to their age and technical condition do not meet modern requirements. This is caused by the fact that before, the regulations were not as strict as they are now, and the construction process was focused on savings rather than heat loss aspects.

Municipal Buildings and Housing Administration of Gdynia has only old paper documentation and this slow down the decision about the renovation. There is no information about the existing building technical and energetic condition. In addition, the housing administration has neither a license for commercial computer-aided design (CAD) nor building information modelling software.

ASHVIN should provide accurate digital twin information of existing building as a baseline for better planning of the renovation process. The goal is to support the building owner and develop a digital twin that accurately describe the energetic behavior of the building. This allows the Investor to select the most suitable and adjusted to the building condition renovation scenario**.**

In Table 5.2 the overview of implemented SHM systems for Demo #2 are presented, which are integrated into ASHVIN DT platform.

Table 5.2 Planned measurements for demonstration site #2.

Type of data	Device/sensor	Rate	Volume	Data format	Data collecting2	Storing of data
Temperature, humidity, CO2, CO, VOC, PM 2.5 and PM 10, pressure	Nanoenvi IAQ device	10 min measurement	0.05GBper year	json	MQTT	Mainflux platform
Wall Temperature	Thermocouples.	1 measurement / hour	10 Mb /year	JSON	MQTT	Mainflux platform

5.1.3 DEMO#3: ZADAR AIRPORT

Zadar airport is one of nine civil airports in Republic Croatia. It is situated in the middle of the Adriatic coast, 7 km east of the City of Zadar (Figure 5.3). Zadar Airport was opened in 1969 as an addition to the existing military runway, and with the construction of a civilian runway, it became the only airport in Croatia with two runways. The airport had a steady growth of traffic during the 1970s and 1980s, when tourism in Croatia, and especially in Dalmatia, reached its peak at the time. However, this was abruptly interrupted by the war in Croatia in the first half of the 1990s, when the Zadar airport was occupied and severely damaged.

After the war the airport was partially repaired. After the post-war renovation traffic grew steadily from 1996 to 2006, from 20.000 to 65.000 passengers. Zadar Airport experienced its new rise in 2007 after which it has not only reached pre-war numbers but has increased traffic tenfold since its renovation reaching more than 800.000 passengers. In 2019, just prior to the COVID-19 decline of airline traffic worldwide Zadar airport was among the top 5 in terms of traffic growth (+37,6% increase in passenger traffic, ACI EUROPE Airport Traffic Report, www.aci-europe.org).

The Zadar Airport is responsible for transport operating services and maintenance and developments regarding airport infrastructure. Traffic infrastructure, which includes all operational areas for receiving and dispatching passengers and aircraft, was built, as already stated above, almost 50 years ago. In that period there were several partial renovations of asphalt surfaces, but no major reconstructions. This means that the essential infrastructure of the airport including runways is not in a very good condition degrading further rapidly, starting to influence the safety of traffic. In addition to its existing runway 04-22 (length of 2000m), the airport is also using all operational areas in the military part of the airport (runway 13-31 (length 2500m, width 45m) , tracks A, H, F, G and K) Zemunik Air Base (which is an air center for the Croatian Air Force).

At the Zadar airport the implementation of UAV for the visual inspection of operational areas will be explored. The aim is to utilize the UAV for infrastructure inspections, which would minimize the impact on airport operations and ensure a full reproducibility and traceability of the records over time. The AI algorithms for crack detection will be then applied and used for the improvement of the existing decision making and maintenance planning of the operational areas.

In Table 5.3 the overview of implemented SHM systems for Demo #3 are presented, which are going to be integrated into ASHVIN DT platform

Figure 5.3: Zadar airport terminal building (left) and runway (right)

Table 1 Planned measurements for demonstration site #3.

Type of data	Device/sensor	Rate	Volume	Data format	Data collecting3	Storing of data
Images	Camera and drone	every 3 months	~100 GB per year	e.g. jpg, point cloud, etc.	Collected data is stored on local server	Local server and Mainflux platform
Environmental data (temperature, humidity, wind	Weather station	Every hour		open source link to xml file4	Open source data	Meteo.hr

5.1.4 DEMO#7: ROAD BRIDGE - BARCELONA AREA

This demonstration site is the PR-04-B015 bridge, that is located within the Metropolitan Area of Barcelona (Spain). Its main objective is to connect two main road axes: the AP-7 Highway (heading North) and the A-2 Road (Heading West), Figure 5.4. This connection belongs to a strategic link for users of those axes whose aim is to avoid urban areas while crossing the Metropolitan Area of Barcelona. The link helps reducing approximately in 12 Kilometers the distance with the present connection between roads. It is a strategic asset for transporting goods from Barcelona port to northern Europe. The PR-04-B015 bridge is a continuous beam drawn on a horizontally curved alignment (Figure 5.4). Two separated viaducts are defined by the driving direction (heading North or West). The structures allow bridging a river (Llobregat), a creek (Rubi), several roads and a line of railways. Both viaducts are supported by 12 piers with varying span. The cross-section is a composite bridge. Box section with variable web height (3,5 m-5,0 m) and a concrete slab with varying width (11,50 m-17,00 m). Longitudinally, the cross-section is provided with stiffeners and transversally, with stiffeners and diaphragms. The total length of the structure is approximately 840 meters.

Figure 5.4: Road bridge. Barcelona Area

In Table 5.4 the overview of implemented SHM systems for Demo #7 are presented, which are integrated into ASHVIN DT platform

Table 2 Planned measurements for demonstration site #7.

Type of data	Device/sensor	Rate	Volume	Data format	Data collecting[5]	Storing of data
Expansion Joints	Laser +- 5 mm	100-to-200 samples per second	2-3 Hours of continuous measurement	Txt	Data from sensors is sent using a HBM MGCPlus data logger.	Locally and then sent to the Mainflux platform.
Inclination	WitMotion WT901B TTL	100-to-200 samples per second	2-3 Hours of continuous measurement	JSON	Data is directly sent to Mainflux using a MQQT	Directly to Mainflux Format
Acceleration	BeanAir (MQQT Protocol). ADX345 + ESP32. Netplus	100-to-200 samples per second	2-3 Hours of continuous measurement	.txt	Data is directly sent to Mainflux using a MQQT	Directly to Mainflux Format
Environmental conditions (Temperature and Humidity)	DHT22	1 samples per minute	2-3 Days of continuous measurement	JSON	Data is directly sent to Mainflux using a MQQT	Directly to Mainflux Format
Initial imperfections (remote sensing)	Terrestrial Laser Scanner	Point Cloud. Millions per hour	Episodic	Point Cloud	TLS local collection	Locally, treated and subsequently sent to Mainflux

Cameras for traffic measurement (anonymized)	DJI Mavic Air 2.	Continuous, Slow motion (180 FPS)	-	.JPG	- local collection	Local drive. Post-processed and sent to Mainflux Platform
Cameras for telemetry	DJI Mavic Air 2.	Continuous, 4K (30 FPS)	-	.MP4	- local collection	Local drive. Post-processed and sent to Mainflux Platform
Thermocouples		Low rate (0,01 continuous)	-	JSON	- Data is directly sent to Mainflux using a MQQT	Mainflux Platform
Space borne data	Sentinel 2. Radar	Daily (Historic)		.JPG .txt	Post-processed data is sent to Mainflux	Mainflux and Ashvin

5.1.5 DEMO#9: MUNICH STADIUM - ROOF

The Olympic Roof in Munich was built for the 1972 Olympic Games and will soon celebrate its 50th anniversary. This impressive cable net structure is, both from an aesthetic - architectural point of view and as a technical venture, an icon of the construction and engineering art of the second half of the 20th century.

The Olympiapark ensemble is one of the most important event venues and sports centres in the south of Germany.

The Olympic tent roof structure consists of four almost independent and highly prestressed cable net constructions (Figure 5.5). In total, the cable net forms a roof area of 74,000m^2. Prior to the upcoming anniversary, a comprehensive structural survey was carried out by sbp (Stuttgart) and Prof. Feix ingenieure (Munich). As part of this investigation, a complete static model of the cable net construction was done by sbp for the first time since the roof's existence. The core task was to determine the existing internal force or pre-stressing state in the cable net structure using novel calculation techniques in combination with cable force measurements.

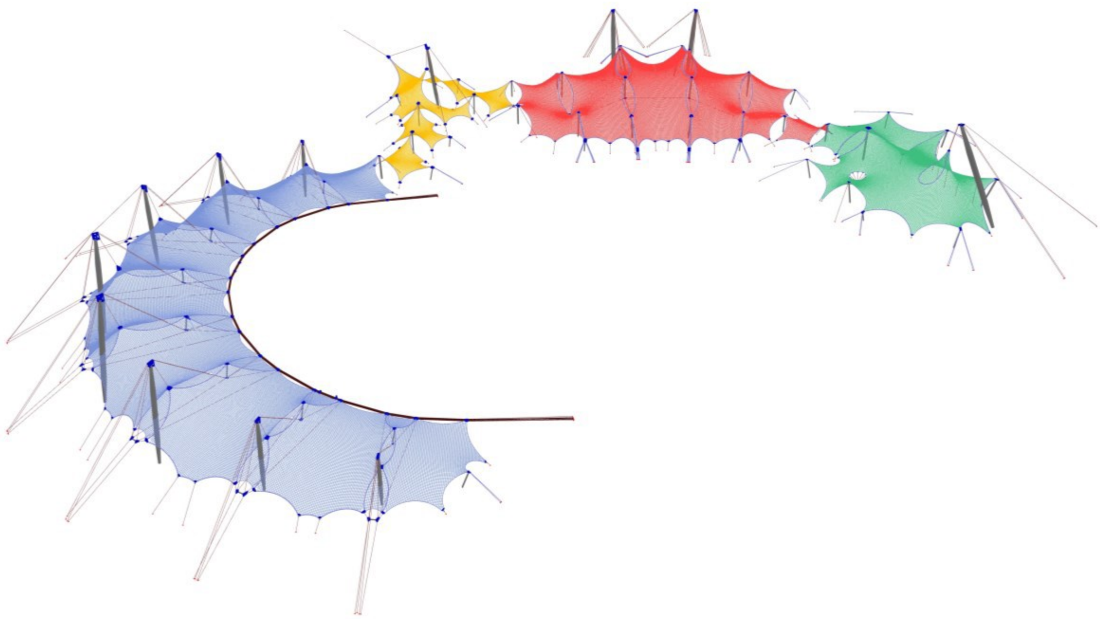


Figure 5.5: Munich Olympic Stadium roof

In Table 5.5 the overview of implemented SHM systems for Demo #9 are presented, which are integrated into ASHVIN DT platform

Table 5.5 Planned measurements for demonstration site #9

Type of data	Device/sensor	Rate	Volume	Data format	Data collecting[6]	Storing of data
Measurement of deflections of the cable net	Terrestrial Laser Scanner	-	-	Point Cloud	-	Data stored in AIP.
Images of the roof cladding (Plexiglas)	Camera and drone	every 3 months	~100 GB per year	e.g. jpg, point cloud, etc.	Not defined yet	not defined yet
Space borne data	Sentinel 2. Radar	Daily (Historic)		.JPG .txt	Post-processed data is sent to Mainflux	Mainflux and Ashvin

6 CONCLUSIONS

The Digital Twin of an asset aimed at maintenance purposes requires a robust and distributed source of data along the physical twin able to gather the asset behaviour and performance. Ideally, the nature of the incoming data/information is varied and multiple. In addition, like in a nervous system, distributed information can be centralized and processed. Therefore, multiple data-gathering techniques are needed. DT requires a massive monitoring capacity and often, cost-efficient sensors are required. In this document, three sources of data to feed the digital representation of the asset have been studied:

- Sensors
- Images
- Remote-sensing techniques

However, for a good performance of the digital twin, raw data coming from sensors, images or via remote techniques should be converted into information that can be used for efficient decision-making. To this end, data should be post-processed and converted into performance indicators and finally into Key Performance Indicators. This can be achieved by an SHM system.

For each of the aforementioned monitoring techniques, as well as for SHM systems, a dissection of requirements for meaningful implementation of a physical asset from the built environment in the form of a Digital Twin has been presented in this deliverable, leading to the following conclusions.

Regarding data collection techniques (sensors, radars, scanners, drones, cameras etc.), apart from the general requirements of accuracy and robustness, inherent to any data collection device, the following specific requirements were identified for an efficient implementation into a DT:

1. Sampling rate
2. Volume of data
3. Data format
4. Data collecting
5. Data storing

In addition, in the case of image-based data and remote sensing, replicability of data is an important issue. In the first case, image-data implies accurate documentation of the spatial location of the camera position or UAV positioning, together with available photographic metadata. Concerning remote sensing, replicability issues are also of great concern if successive scans are performed in time. Spatial location and referring to the point clouds is of an utmost importance too. These requirements have been reported and quantified based on their application to several demonstration projects dealt with in the ASHVIN project as presented in chapter 5.

Concerning SHM Systems, specific requirements for DT application were identified as follows:

1. The SHM system should be distributed along the structure / built asset in order to be able to monitor as many areas of the physical twin as possible. Redundant information is desirable. The SHM should be scalable

2. When fast response is required from the DT, the SHM system should be fast in gathering and analysing the data.
3. It is also required to be comprehensive, in the sense that the analysis of the gathered data by the SHM system should be exhaustive and able to discover any defect even if not thought to be present.
4. Ability to acquire the signal from a high number of sensors and to generate proper input signals to command the response of the DT.
5. Autonomy of the system regarding possible ways to obtain energy for their operation
6. An important aspect of the monitoring system is the requirement of full synchronization between physical and digital assets.
7. The SHM must provide monitoring data in a way that can be integrated within data models that can guarantee interoperability (ability to effectively, accurately, and consistently communicate and exchange information, within different information technology Systems) among digital systems.
8. Auto-checking: The system must integrate procedures to automatically detect outliers and how some non-expected data can be interpreted as a malfunction of the monitoring system itself rather than as a malfunction of the physical twin.

7 REFERENCES

Abbas Y., Have B., Hoekstra G., Douma A., de Bruijn D., Olthuis W., Van den Berg A. (2015). Connecting to Concrete: Wireless Monitoring of Chloride ions in Concrete structures. Procedia Engineering 120: 965 – 968

Abdeljaber O., Avci O., Kiranyaz M.S., Boashash B., Sodano H., Inman D.J. (2018). 1-D CNNs for structural damage detection: verification on a structural health monitoring benchmark data. Neurocomputing 275:1308–1317

Abdulkarem M., Samsudin K., Rokhani F.Z., A Rasid M.F. (2020). Wireless sensor network for structural health monitoring: A contemporary review of technologies, challenges, and future direction. Structural Health Monitoring, 19(3): 693–735. DOI: 10.1177/1475921719854528

Adhikari R.S, Zhu Z., Moselhi O., Bagchi A. (2013). Automated Bridge Condition Assessment with Hybrid Sensing. 30th International Symposium on Automation and Robotics in Construction and Mining; Held in conjunction with the 23rd World Mining Congress, 10.22260/ISARC2013/0142.

Aiger D., Mitra N. J., Cohen-Or D. (2008). 4-points congruent sets for robust pairwise surface registration. In ACM SIGGRAPH 2008 papers (pp. 1-10).

Allaire S., Kim J. J., Breen S. L., Jaffray D. A., Pekar V. (2008). Full orientation invariance and improved feature selectivity of 3D SIFT with application to medical image analysis. In 2008 IEEE computer society conference on computer vision and pattern recognition workshops (pp. 1-8). IEEE.

Alonso M.C., Puentes J. (2020). Self-Compacted Concrete with Self-Protection and Self-Sensing Functionality for Energy Infrastructures. Materials, 13, 1106. DOI: 10.3390/ma13051106

Alver N., Ozevin D. (2021). Civil infrastructure monitoring with quantitative acoustic emission methods. Proceedings of the 10th International Conference on Structural Health Monitoring of Intelligent Infrastructure, SHMII 10, Porto, Portugal.

Alwis L.S.M., Bremer K., Roth B. (2021). Fiber Optic Sensors Embedded in Textile-Reinforced Concrete for Smart Structural Health Monitoring: A Review. Sensors, 21, 4948. DOI: 10.3390/s21154948

Artese S., Zinno, R. (2020). TLS for dynamic measurement of the elastic line of bridges. Applied Sciences, 10(3), 1182.

Aryan A., Bosché F., Tang, P. (2021). Planning for terrestrial laser scanning in construction: A review. Automation in Construction, 125, 103551.

Asif K., Zhang L., Derrible S., Indacochea J.E., Ozevin D., Ziebart B. (2020). Machine learning model to predict welding quality using air-coupled acoustic emission and weld inputs. Journal of Intelligent Manufacturing. DOI: 10.1007/s10845-020-01667-x

Avci O., Abdeljaber O., Kiranyaz S., Hussein M., Gabbouj M., Inman D. (2021). A review of vibration-based damage detection in civil structures: From traditional methods to Machine Learning and Deep Learning applications. Mechanical Systems and Signal Processing, 147, 107077. DOI: 10.1016/j.ymssp.2020.107077

Azimi M., Pekcan G. (2020) Structural health monitoring using extremely compressed data through deep learning. Computer Aided Civil Infrastructure 35:597–614. DOI: 10.1111/mice.12517

Bado M., Casas J.R. (2021). A Review of Recent Distributed Optical Fiber Sensors Applications for Civil Engineering Structural Health Monitoring. Sensors, 21, 1818. DOI: 10.3390/s21051818

Barrias A., Casas J.R., Villalba S. (2016). A Review of Distributed Optical Fiber Sensors for Civil Engineering Applications. Sensors , 16, 748. DOI: 10.3390/s16050748

Barrile, V., Candela, G., Fotia, A. (2019) Point Cloud Segmentation using Image Processing Techniques for Structural Analysis, https://doi.org/10.5194/isprs-archives-XLII-2-W11-187-2019.

Berrocal C., Fernandez I., Bado M., Casas J.R., Rempling R. (2021). Assessment and visualization of performance indicators of reinforced concrete beams by distributed optical fibre sensing. Structural Health Monitoring, 20(6): 3309-3326. DOI: 10.1177/1475921720984431

Bello S. A., Yu S., Wang C., Adam J. M., Li, J. (2020). Deep learning on 3D point clouds. Remote Sensing, 12(11), 1729.

Besl P., McKay H. (1992). A method for registration of 3-D shapes. IEEE Trans. Pattern Anal. Mach. Intell. 14(2): 239–256

Bogomolov D., Testoni N., Zonzini F., Malatesta M., De Marchi L., Marzani A. (2021). Acoustic emission structural monitoring through low-cost sensor nodes. Proceedings of the 10th International Conference on Structural Health Monitoring of Intelligent Infrastructure, SHMII 10. Porto, Portugal.

Boje C., Guerrieroa A., Kubickia S., Rezguib Y. (2020). Towards a semantic Construction Digital Twin: Directions for future research. Automation in Construction, 114, 103179. DOI: 10.1016/j.autcon.2020.103179.

Bosché, F. (2012). Plane-based registration of construction laser scans with 3D/4D building models. Advanced Engineering Informatics, 26(1): 90-102.

Bosché, F., Ahmed M., Turkan Y., Haas C., Haas R. (2015). The value of integrating Scan-to-BIM and Scan-vs-BIM techniques for construction monitoring using laser scanning and BIM: The case of cylindrical MEP components. Automation in Construction, 49: 201-213.

Bueno, M., Bosché, F., González-Jorge, H., Martínez-Sánchez, J., Arias, P. (2018). 4-Plane congruent sets for automatic registration of as-is 3D point clouds with 3D BIM models. Automation in Construction, 89: 120-134.

Bukhsh A. Z., Jansen N., Saeed A. (2021). Damage detection using in-domain and cross-domain transfer learning. Neural Computing and Applications 33(3).DOI:10.1007/s00521-021-06279-x

Bukhsh A. Z., Anzlin, A. Stipanovic, I. (2022) BiNet: Bridge Visual Inspection Dataset and Approach for Damage Detection. Proceedings of the 1st Conference of the European Association on Quality Control of Bridges and Structures, 1027-1034.

Cabaleiro, M., Riveiro, B., Arias, P., Caamaño, J. C. (2015). Algorithm for beam deformation modeling from LiDAR data. Measurement, 76: 20-31.

Cabaleiro, M., Riveiro, B., Arias, P., Caamaño, J. C. (2016). Algorithm for the analysis of deformations and stresses due to torsion in a metal beam from LIDAR data. Structural Control and Health Monitoring, 23(7): 1032-1046.

Carrihlo A. C., Galo, M., Santos, R. C. (2018). Statistical outlier detection method for airborne lidar data. International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences.

Castañeda-Saldarriaga D., Alvarez-Montoya J., Martínez-Tejada V., Sierra-Pérez J. (2021)._Toward Structural Health Monitoring of Civil Structures Based on Self-Sensing Concrete Nanocomposites: A Validation in a Reinforced-Concrete Beam. Int J Concr Struct Mater 15(3). DOI: 10.1186/s40069-020-00451-8

Castellani U., Bartoli A. (2020) 3D Shape Registration. In: Liu Y., Pears N., Rosin P.L., Huber P. (eds) 3D Imaging, Analysis and Applications. Springer, Cham. DOI: 10.1007/978-3-030-44070-1_8

Cha G., Sim S. H., Park S., Oh T. (2020). LiDAR-based bridge displacement estimation using 3D spatial optimization. Sensors, 20(24), 7117.

Cha G., Park S., Oh T. (2019). A terrestrial lidar-based detection of shape deformation for maintenance of bridge structures. Journal of Construction Engineering and Management, 145(12), 04019075.

Chan, B., Guan, H., Jo, J., Blumenstein, M. (2015) Towards UAV-based bridge inspection systems: a review and an application perspective, Struct. Monit. Maint. 2 (3) 283–300, http://dx.doi.org/10.12989/smm.2015.2.3.283.

Chu C., Ghrib F., Cheng S. (2021). Cable tension monitoring through feature-based video image processing. Journal of Civil Structural Health Monitoring 11:69–84 DOI: 10.1007/s13349-020-00438-9

CIRIA (2020). Structural Health Monitoring in Civil Engineering. CIRIA Report C788. London

COST (2019). Report of the innovation subgroup of COST action TU 1406. Brussels.

CDBB (2018). The Gemini Principles. Centre of Digital Built Britain. Digital Framework Task Group, UK

Czerniawski T., Nahangi M., Haas C., Walbridge S. (2016). Pipe spool recognition in cluttered point clouds using a curvature-based shape descriptor. Automation in Construction, 71, 346-358.

D'Amico F., Ggliardi V., Ciampoli L.B., Tosti F. (2020). INtegration of InSAR and GPR techniques for monitoring transition areas in railway bridges. NDTE and E International 115, 102291. DOI: 10.1016/j.ndteint.2020.102291.

Dai K., Boyajian D., Liu W., Chen S.E., Scott J., Schmieder M.(2014). Laser-based field measurement for a bridge finite-element model validation. Journal of Performance of Constructed Facilities, 28(5), 04014024. DOI: 10.1061/(ASCE)CF.1943-5509.0000484

Das S., Saha P. (2018). A review of some advanced sensors used for health diagnosis of civil engineering structures. Measurement, 129, 68–90. DOI: 10.1016/j.measurement.2018.07.008

Davila J.M., Butler L.J., Gibbons N., Brilakis I., Elshafie M., Middleton C. (2017). Management of structural monitoring data of bridges using BIM. Proceedings of the Institution of Civil Engineers, Bridge Engineering 170 (BE3): 204–218. DOI: 10.1680/jbren.16.00013

Davila J.M., Butler L.J., Brilakis I., Elshafie M., Middleton C., (2018). Structural Performance Monitoring Using a Dynamic Data-Driven BIM Environment. Journal of Computing in Civil Engineering, 04018009. DOI: 10.1061/(ASCE)CP.1943-5487.0000749

Davila J.M. and Oyedele L. (2021). Digital Twins for the built environment: learning from conceptual and process models in manufacturing. Advanced Engineering Informatics, 49, 101332. DOI: 10.1016/j.aei.2021.101332.

Dong C. Z. , Catbas F. (2020). A review of computer vision–based structural health monitoring at local and global levels. Structural Health Monitoring, 20(2): 692–743. DOI: 10.1177/1475921720935585

Dong C.Z., Celik O., Catbas F. (2019). Marker-free monitoring of the grandstand structures and modal identification using computer vision methods. Structural Health Monitoring 18(5-6): 1491–1509. , DOI: 10.1177/1475921718806895

Ellenberg A., Branco L., Krick A., Bartoli I., Kotsos T. (2014). Use of Unmanned Aerial Vehicle for Quantitative Infrastructure Evaluation. Journal of Infrastructure Systems. 21(3).

Ercolessi S., Fabbrocino G., Rainier C. (2021). Indirect Measurements of Bridge Vibrations as an Experimental Tool Supporting Periodic Inspections. Infrastructures, 6, 39. DOI: 10.3390/infrastructures6030039

Erdélyi J., Kopáčik A., Lipták I., Kyrinovič P. (2017). Automation of point cloud processing to increase the deformation monitoring accuracy. Applied Geomatics, 9(2): 105-113.

Erdélyi J., Kopáčik A., Kyrinovič P. (2020). Spatial data analysis for deformation monitoring of bridge structures. Applied Sciences, 10(23), 8731.

Fan L., Tan X., Zhang Q., Meng W., Chen G., Bao Y. (2020). Monitoring corrosion of steel bars in reinforced concrete based on helix strains measured from a distributed fiber optic sensor. Engineering Structures, 204, 110039. DOI: 10.1016/j.engstruct.2019.110039

Fan L., Bao Y. (2021) Review of fiber optic sensors for corrosion monitoring in reinforced concrete. Cement and Concrete Composites, 120, 104029. DOI: 10.1016/j.cemconcomp.2021.104029

Fargnoli M., Lleshaj A., Lombardi M., Sciarretta N., Di Gravio G. (2019). A BIM-based PSS approach for the management of maintenance operations of building equipment. Buildings, 9 (6). DOI: 10.3390/buildings9060139

Feng D., Feng M.Q., Ozer E, et al. (2015). A vision-based sensor for noncontact structural displacement measurement. Sensors, 15, 16557–16575

Feng M., Fukuda Y., Mizuta M., Ozer E. (2015). Citizen sensors for SHM: Use of accelerometer data from smartphones. Sensors, 15, 2980–2998. DOI: 10.3390/s150202980

FHWA. (2014). State of the practice and art for structural health monitoring of bridge substructures. Federal Highway Administration. McLean, VA (USA).

Foltz B. (2000). Application: 3D laser scanner provides benefits for PennDOT bridge and rockface surveys. Prof. Surv., 20(5): 22–28.

Gabai H.,Eyal A. (2016). On the sensitivity of distributed acoustic sensing. Optics Letters, 41(24): 5648-5651

Gkantou M. et al. (2019). Novel Electromagnetic Sensors Embedded in Reinforced Concrete Beams for Crack Detection. Sensors, 19, 5175. DOI: 10.3390/s19235175

Gkoumas K., Gkoktsi K, Bono F, Galassi M.C., Tirelli D. (2021). The Way Forward for Indirect Structural Health Monitoring (iSHM) Using Connected and Automated Vehicles in Europe. Infrastructures, 6, 43. DOI: 10.3390/infrastructures 6030043

Górski M., Krzywoń R., Borodeńko M. (2018). Development of Self-Sensing Textile Strengthening System Based on High-Strength Carbon Fiber. Materials, 11(10), 2062

Gunay H.B., Shen W., Newsham G. (2019). Data analytics to improve building performance: a critical review, Automation in Construction. 97, 96–109. DOI: 10.1016/j.autcon.2018.10.020

Guo X., Xiao J. & Wang Y (2018). A survey on algorithms of hole filling in 3D surface reconstruction. Vis Comput 34, 93–103. DOI: 10.1007/s00371-016-1316-y

Ha D.W., Park H.S., Choi S.W., Kim Y. (2013). A Wireless MEMS-Based Inclinometer Sensor Node for Structural Health Monitoring. Sensors, 13, 16090-16104. DOI: 10.3390/s131216090

Hester D., González A. (2017). A discussion on the merits and limitations of using drive-by monitoring to detect localised damage in a bridge. Mechanical Systems and Signal Processing, 90, 234-253. DOI: 10.1016/j.ymssp.2016.12.012

Hiasa S., Birgul R., Matsumoto M., Catbas N. (2018). Experimental and numerical studies for suitable infrared thermography implementation on concrete bridge decks. Measurement. 121, 144-159.

Hiasa S., Catbas N., Matsumoto M., Mitani K. (2017). Considerations and Issues in the Utilization of Infrared Thermography for Concrete Bridge Inspection at Normal Driving Speeds. Journal of Bridge Engineering. 22(11).

Hoppe E. J., Novali F., Rucci A., Fumagalli A., Del Conte S., Falorni G.,Toro N. (2019). Deformation monitoring of posttensioned bridges using high-resolution satellite remote sensing. Journal of Bridge Engineering, 24(12), 04019115

Huang Q., Wang Y., Luzi G., Crosetto M., Monserrat O., Jiang J., ...,Ding, Y. (2020). Ground-Based Radar Interferometry for Monitoring the Dynamic Performance of a Multitrack Steel Truss High-Speed Railway Bridge. Remote Sensing, 12(16), 2594.DOI: 10.3390/rs12162594

Huthwohl P., Brilakis I., Borrmann A., Sacks, R. (2018). Integrating RC bridge defect information into BIM models. Journal of Computing in Civil Engineering, 32(3), 04018013. DOI: 10.1061/(ASCE)CP.1943-5487.0000744

Isailović, D., Stojanovic, V., Trapp, M., Richter, R., Hajdin, R., Döllner, J. (2020). Bridge damage: Detection, IFC-based semantic enrichment and visualization, Automation in Construction, 112. DOI: 10.1016/j.autcon.2020.103088.

Islam M.M., Kim J.M. (2019). Vision-Based Autonomous Crack Detection of Concrete Structures Using a Fully Convolutional Encoder–Decoder Network. Sensors 19, 4251. DOI: 10.3390/s1919425

Jiajing L., Zhaoyong W., Bin L.., Xiao W., Luchuan L., Qing Y., Ronghui Q., Haiwen C. (2019). Distributed acoustic sensing for 2D and 3D acoustic source localization. Optics Letters, 44(7): 1690-1693

Kanezaki A., Matsushita Y., Nishida Y. (2018). Rotationnet: Joint object categorization and pose estimation using multiviews from unsupervised viewpoints. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 5010-5019).

Kang K., Lin J., Zhang J. (2018). BIM- and IoT-based monitoring framework for building performance management, J. Struct. Integrity Maint. 3 (4): 254–261. DOI: 10.1080/24705314.2018.1536318

Khodabandehlou H., Pekcan G., Fadali M.S. (2019) Vibration-based structural condition assessment using convolution neural networks. Struct Control Health Monit 26(2), e2308

Kim H., Kim, C. (2020). Deep-Learning-Based Classification of Point Clouds for Bridge Inspection. Remote Sensing, 12(22), 3757.

Kim H., Kim, C. (2021). 3D as-built modeling from incomplete point clouds using connectivity relations. Automation in Construction, 130, 103855.

Korumaz M., Betti M., Conti A., Tucci G., Bartoli G., Bonora, V., Fiorini L. (2017). An integrated Terrestrial Laser Scanner (TLS), Deviation Analysis (DA) and Finite Element (FE) approach for health assessment of historical structures. A minaret case study. Engineering Structures, 153, 224-238.

Krizhevsky A., Sutskever I., Hinton G.E. (2012). Imagenet classification with deep convolutional neural networks. In: Advances in neural information processing systems, 1097–1105

Kromanis, R., Al-Habaibeh, A. (2017). Low cost vision-based systems using smartphones for measuring deformation in structures for condition monitoring and asset management, in SHMII 2017 - 8th International Conference on Structural Health Monitoring of Intelligent Infrastructure, Proceedings (International Society for Structural Health Monitoring of Intelligent Infrastructure, ISHMII), 430–440.

Kromanis R., Xu Y., Lydon D., Martinez del Rincon J. and Al-Habaibeh A. (2019). Measuring Structural Deformations in the Laboratory Environment Using Smartphones. Front. Built Environ. 5(44). DOI: 10.3389/fbuil.2019.00044

Krzywon R., Gorsk M., Dawczynski S., Szojda L., Castro-Gomes J., Salvado R. (2016). Self-Monitoring Strengthening System Based on Carbon Fiber Laminate. Journal of Sensors, 2016, 3947513. DOI: 10.1155/2016/3947513

Lemmens M. (2011) Terrestrial Laser Scanning. In: Geo-information. Geotechnologies and the Environment, vol 5. Springer, Dordrecht. DOI: 10.1007/978-94-007-1667-4_6

Lin K., Xu Y-L, Lu X., Guan Z., Li J. (2021). Digital twin-based collapse fragility assessment of a long-span cable-stayed bridge under strong earthquakes. Automation in Construction, 123, 103547

Liu W., Sun J., Li W., Hu T. & Wang P. (2019). Deep learning on point clouds and its application: A survey. Sensors, 19(19), 4188.

Loupos K., Damigos Y., Amditis A., Gerhard R., Rychkov D., Wirges W., Schulze M., Lenas S-A, Chatziandreoglou C., Malliou C.M., Tsaoussidis V., Brady K., Frankenstein

B. (2017). Structural health monitoring system for bridges based on skin-like sensor. IOP Conf. Series: Materials Science and Engineering 236, 012100. DOI:10.1088/1757-899X/236/1/012100

Lu R., Brilakis I. (2019). Digital twinning of existing reinforced concrete bridges from labelled point clusters. Automation in Construction, 105, 102837. DOI: 10.1016/j.autcon.2019.102837

Lu Q., Chen L., Lid S., Pitta M. (2020a). Semi-automatic geometric digital twinning for existing buildings based on images and CAD drawings. Automation in Construction, 115, 103183. DOI: 10.1016/j.autcon.2020.103183

Lu Q., Xie X., Parlikad A.K., Schooling J.M. (2020b). Digital twin-enabled anomaly detection for built asset monitoring in operation and maintenance. Automation in Construction, 118, 103277. DOI: 10.1016/j.autcon.2020.103277

Lydon, D., Lydon, M., Taylor, S., Del Rincon, J. M., Hester, D., and Brownjohn, J. (2019). Development and field testing of a vision-based displacement system using a low cost wireless action camera,. Mech. Syst. Signal Process. 121, 343–358. doi:10.1016/j.ymssp.2018.11.015

Ma J. W., Czerniawski T., Leite, F. (2020). Semantic segmentation of point clouds of building interiors with deep learning: Augmenting training datasets with synthetic BIM-based point clouds. Automation in construction, 113, 103144.

Malekjafarian A., McGetrick P.J., OBrien E.J. (2015). A Review of Indirect Bridge Monitoring Using Passing Vehicles. Shock and Vibration, 2015, 286139. DOI: 10.1155/2015/286139

Matsumoto M., Mitani K., Catbas N., Hiasa S. (2014). Non-destructive Structural Assessment Method using Imaging technology and Infrared Thermography. IABSE Symposium: Engineering for Progress, Nature and People, Madrid, Spain.

Maturana D., Scherer S. (2015). Voxnet: A 3d convolutional neural network for real-time object recognition. In 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 922-928. IEEE.

Mei Q., Gül M. (2019). A crowdsourcing-based methodology using smartphones for bridge health monitoring. Structural Health Monitoring, 18 (5–6): 1602–1619. DOI: 10.1177/1475921718815457

Mei Q., Gül M, Boay M. (2019). Indirect health monitoring of bridges using Mel-frequency cepstral coefficients and principal component analysis. Mech. Syst. Sig. Process. 119: 523–546. DOI: 10.1016/j.ymssp.2018.10.006

Mellado N., Aiger D., Mitra N. J. (2014). Super 4pcs fast global pointcloud registration via smart indexing. In Computer graphics forum, 33(5): 205-215.

Miccinesi L., Beni A., Pieraccini M. (2021). Multi-monostatic interferometric radar for bridge monitoring. Electronics, 10(3), 247. DOI: 10.3390/electronics10030247

Mistretta F., Sanna G., Stochino F., Vacca, G. (2019). Structure from motion point clouds for structural monitoring. Remote Sensing, 11(16), 1940.

Morgenthal G., Rau S., Taraben J., Abbas T. (2018). Determination of stay-cable forces using highly mobile vibration measurement devices. J. Bridge Eng. 23 (2), 04017136. DOI: 10.1061/(ASCE)BE.1943-5592.0001166

Navabian N., Beskhyroun S., Matulich J. (2020). Development of wireless smart sensor network for vibration-based structural health monitoring of civil structures. Structure and Infrastructure Engineering. DOI: 10.1080/15732479.2020.1850801

Nguyen A., Le B. (2013) 3D point cloud segmentation: a survey. 6th IEEE conference on robotics, automation and mechatronics (RAM). IEEE

Ni F.T., Zhang J., Chen Z.Q. (2019). Pixel-level crack delineation in images with convolutional feature fusion. StructControl Heal Moni, 26: 1–18

NIC (2017). Data as infrastructure – paper for the National Infrastructure Commission. National Infrastructure Commission, London, UK

Noel A.B., Abdaoui A., Elfouly T., Ahmed M., Badawy A., Shehata M. (2017). Structural Health Monitoring Using Wireless Sensor Networks: A Comprehensive Survey. IEEE Communications Surveys & Tutorials, 19 (3): 1403-1423. DOI: 10.1109/COMST.2017.2691551

Obiechefu, C. B., & Kromanis, R. (2021). Damage detection techniques for structural health monitoring of bridges from computer vision derived parameters. Structural Monitoring and Maintenance, 8(1), 91-110.

Olaszek P.,Casas J.R., Swit G. (2016). On-site assessment of bridges supported by acoustic emission. Proceedings of the Institution of Civil Engineers, Bridge Engineering, 169(BE2): 81-92. DOI: 10.1680/jbren.15.00007

Oliveira H., Correia P. L. (2014). CrackIT - An image processing toolbox for crack detection and charecterisation. Proc. IEEE International Conf. on Image Processing - ICIP, Paris, France.

Omar T., Nehdi M.L. (2017). Remote sensing of concretebridge decks using unmanned aerial vehicle infrared thermography. Automation in Construction, 83: 360–371

Park K.T., Lee D., Do Noh S. (2020). Operation Procedures of a Work-Center-Level Digital Twin for Sustainable and Smart Manufacturing, Int. J. Precision Eng. Manufact. Green Technol. 7, 791–814. DOI: 10.1007/s40684-020-00227- 1

Pazhoohesh M., Zhang C., Hammad A., Taromi Z., Razmjoo A. (2021). Infrared thermography for a quick construction progress monitoring approach in concrete structures. Architecture, Structures and Construction. DOI: 10.1007/s44150-021-00008-7

Perez-Perez Y., Golpavar-Fard M., El-Rayer K. (2021). Scan2BIM-NET: Deep Learning Method fos Segmentation of Point Clouds for Scan-to-BIM. Journal of Construction Engineering and Management, 147(9).

Pieraccini M., Miccinesi L., Abdorazzagh Nejad A., Naderi Nejad Fard A. (2019). Experimental dynamic impact factor assessment of railway bridges through a radar interferometer. Remote Sensing, 11(19), 2207. DOI: 10.3390/rs11192207

Pierdicca R., Paolanti M., Matrone F., Martini M., Morbidoni C., Malinvern, E. S., ... , Lingua, A. M. (2020). Point cloud semantic segmentation using a deep learning framework for cultural heritage. Remote Sensing, 12(6), 1005.

Ponzo F. C., Iacovino C., Ditommaso R., Bonano M., Lanari R., Soldovieri F., ...,Rompato, M. (2020). Transport Infrastructure SHM Using Integrated SAR Data and On-Site Vibrational Acquisitions:“Ponte Della Musica–Armando Trovajoli” Case Study. Applied Sciences, 11(14), 6504. DOI: 10.3390/app11146504

Pu S., Vosselman G. (2009) Knowledge based reconstruction of building models from terrestrial laser scanning data. ISPRS J Photogramm Remote Sens 64(6):575–584

Qi C. R., Su H., Nießner M., Dai A., Yan M., Guibas L. J. (2016). Volumetric and multi-view cnns for object classification on 3d data. In Proceedings of the IEEE conference on computer vision and pattern recognition, 5648-5656.

Qi C. R., Su H., Mo K., Guibas, L. J. (2017a). Pointnet: Deep learning on point sets for 3d classification and segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition, 652-660.

Qi C. R., Yi L., Su H., Guibas L. J. (2017b). Pointnet++: Deep hierarchical feature learning on point sets in a metric space. arXiv preprint arXiv:1706.02413.

Qin X., Ding X., Liao M., Zhang L., Wang C. (2019). A bridge-tailored multi-temporal DInSAR approach for remote exploration of deformation characteristics and mechanisms of complexly structured bridges. ISPRS Journal of Photogrammetry and Remote Sensing, 156, 27-50.

Radhika K., Vishalini P. (2016). DIGITAL IMAGE PROCESSING – Sequence, Components and Pros. International Journal of Computer Science and Information Technologies, 7 (2): 922-924.

Rashidi A., Brilakis I. (2016). Point Cloud Data Cleaning and Refining for 3D As-Built Modeling of Built Infrastructure. DOI: 10.1061/9780784479827.093.

Riegler G., Osman Ulusoy A., Geiger A. (2017). Octnet: Learning deep 3d representations at high resolutions. In Proceedings of the IEEE conference on computer vision and pattern recognition, 3577-3586.

Riveiro B., González-Jorge H., Varela M., Jáuregui, D. V. (2013). Validation of terrestrial laser scanning and photogrammetry techniques for the measurement of vertical underclearance and beam geometry in structural inspection of bridges. Measurement, 46(1): 784-794.

Riveiro, B., Jauregui, D. V., Arias, P., Armesto, J., Jiang, R. (2012). An innovative method for remote measurement of minimum vertical underclearance in routine bridge inspection. Automation in Construction, 25, 34-40

Rodríguez G., Casas, J.R., Villalba S. (2019a). Shear crack width assessment in concrete structures by 2D distributed optical fiber. Engineering Structures, 195, 508-523

Rodríguez G., Casas, J.R., Villalba S. (2019b). Shear crack pattern identification in concrete elements via distributed optical fibre grid. Structure and Infrastructure Engineering, 15 (12): 1630-1648

Rosenthal A., Razansky D., Ntziachristos V. (2011). High-sensitivity compact ultrasonic detector based on a pi-phase-shifted fiber Bragg grating. Opt. Lett. 2011, 36, 1833–1835

Rusu R. B., Blodow N., Marton Z. C., Beetz M. (2008). Aligning point cloud views using persistent feature histograms. In 2008 IEEE/RSJ international conference on intelligent robots and systems, 3384-3391.

Rusu R. B., Blodow N., Beetz M. (2009). Fast point feature histograms (FPFH) for 3D registration. In 2009 IEEE international conference on robotics and automation, 3212-3217.

Sánchez-Rodríguez A., Riveiro B., Conde B., Soilán M. (2018). Detection of structural faults in piers of masonry arch bridges through automated processing of laser scanning data. Structural Control and Health Monitoring, 25(3), e2126.

Sánchez-Aparicio L. J., Riveiro B., Gonzalez-Aguilera D., Ramos, L. F. (2014). The combination of geomatic approaches and operational modal analysis to improve calibration of finite element models: A case of study in Saint Torcato Church (Guimarães, Portugal). Construction and Building Materials, 70: 118-129.

Sapp D. (2015), Whole building design guide. http://www.wbdg.org/om/om.php, Accessed date: 8 February 2022.

Saravanakumar K., Suresh C., Arumugam V. (2021). Damage monitoring of glass/epoxy laminates with different interply fiber orientation using acoustic emission. Structural Health Monitoring, 20(2): 445–455. DOI: 10.1177/1475921720939064

Schögl M., Widhalm B., Avian, M. (2021). Comprehensive time-series analysis of bridge deformation using differential satellite radar interferometry based on Sentinel-1. ISPRS Journal of Photogrammetry and Remote Sensing, 172: 132-146. DOI: 10.1016/j.isprsjprs.2020.12.001

Seo, J., Duque, L., Wacker, J. (2018). Drone-enabled bridge inspection methodology and application, Automation in Construction, (94), 112-126, ISSN 0926-5805, https://doi.org/10.1016/j.autcon.2018.06.006.

Shim C.S., Dang N.S., Lon S., Jeon C.H. (2019). Development of a bridge maintenance system for prestressed concrete bridges using 3D digital twin model. Structure and Infrastructure Engineering 15 (10): 1319–1332. DOI: 10.1080/15732479.2019.1620789.

Shin H. K., Ahn Y. H., Lee S. H., Kim H. Y. (2020). Automatic Concrete Damage Recognition Using Multi-Level Attention Convolutional Neural Network, Materials 2020, 13(23), 5549. DOI: 10.3390/ma13235549

Shirzad-Ghaleroudkhani N., Mei Q, Gül M. (2020). Frequency Identification of Bridges Using Smartphones on Vehicles with Variable Features. J. Bridge Eng (ASCE), 25(7), 04020041. DOI: 10.1061/(ASCE)BE.1943-5592.0001565.

Siringoringo D.M., Fujino Y. (2012). Estimating bridge fundamental frequency from vibration response of instrumented passing vehicle: Analytical and experimental study. Adv. Struct. Eng., 417–433

Solomon C., Breckon T. (2011). Fundamentals of Digital Image Processing. A Practical Approach with Examples in Matlab. Wiley-Blackwell, 2011, ISBN 9780470844724

Su H., Maji S., Kalogerakis E., Learned-Miller E. (2015). Multi-view convolutional neural networks for 3d shape recognition. In Proceedings of the IEEE international conference on computer vision, 945-953.

Tallman T.N., Smyl D.J. (2020). Structural health and condition monitoring via electrical impedance tomography in self-sensing materials: a review. Smart Materials and Structures, 29(12), 123001. DOI: 10.1088/1361-665X/abb352

Tan Y., Zhang L. (2020). Computational methodologies for optimal sensor placement in structural health monitoring: A review. Structural Health Monitoring, 19(4):1287–1308. DOI: 10.1177/1475921719877579

Tang P., Huber D., Akinci B., Lipman R., Lytle A. (2010). Automatic reconstruction of as-built building information models from laser-scanned point clouds: A review of related techniques. Automation in construction, 19(7): 829-843.

Taheri S. (2019). A review on five key sensors for monitoring of concrete structures. Construction and Building Materials, 204, 492–509

Te G., Hu W., Zheng A., Guo, Z. (2018). Rgcnn: Regularized graph cnn for point cloud segmentation. In Proceedings of the 26th ACM international conference on Multimedia, 746-754.

Theiler P. W., Wegner J. D., Schindler K. (2014). Keypoint-based 4-points congruent sets–automated marker-less registration of laser scans. ISPRS journal of photogrammetry and remote sensing, 96, 149-163.

Thirumalaiselvi A., Sasmal S. (2021). Pattern recognition enabled acoustic emission signatures for crack characterization during damage progression in large concrete structures. Applied Acoustics 175, 107797.

Tibaduiza-Burgos D., Gomez-Vargas R., Pedraza C., Agis D., Pozo F. (2020). Damage identification in Structural Health Monitoring: A Brief Review from its Implementation to the Use of Data-Driven Applications. Sensors , 20, 733, DOI: 10.3390/s20030733.

Tibaduiza D. A., Mujica L. E., Anaya M., Rodellar J., Guemes A. (2012). Principal Component Analysis vs. Independent Component Analysis for Damage Detection. 6th European Workshop on Structural Health Monitoring, July 3-6, 2012, Dresden, Germany

Tonelli D., Luchetta M., Rossi F., Migliorino P., Zonta D. (2020). Structural Health Monitoring Based on Acoustic Emissions: Validation on a Prestressed Concrete Bridge Tested to Failure. Sensors, 20, 7272. DOI: 10.3390/s20247272

Trzcinski T., Christoudias M., Fua P., Lepetit V. (2013). Boosting binary keypoint descriptors. In: Computer vision and pattern recognition (CVPR), 2013 IEEE conference on, IEEE, 2874–2881

Vijayan S., Geethalakshmi S.N. (2018). A Survey on Crack Detection Using Image Processing Techniques and Deep Learning Algorithms. International Journal of Pure and Applied Mathematics, 118 (8): 215-220

Villacorta J., Del-Val L., Martínez R., Balmori J.A., Magdaleno A., López G., Izquierdo A., Lorenzana A., Basterra L.A. (2021). Design and Validation of a Scalable, Reconfigurable and Low-Cost Structural Health Monitoring System. Sensors, 21, 648. DOI: 10.3390/s21020648

Wang Q., Kim, M.K., (2019). Applications of 3D point cloud data in the construction industry: A fifteen-year review from 2004 to 2018. Advanced Engineering Informatics, 39, 306-319. DOI: 10.1016/j.aei.2019.02.007

Wang Q., Tan Y., Mei, Z. (2020). Computational Methods of Acquisition and Processing of 3D Point Cloud Data for Construction Applications. Arch Computat. Methods Eng 27, 479–499. DOI: 10.1007/s11831-019-09320-4

Wang Y., Sun Y., Liu Z., Sarma S. E., Bronstein M. M., Solomon J. M. (2019). Dynamic graph cnn for learning on point clouds. Acm Transactions On Graphics, 38(5): 1-12.

Watase A., Birgul R., Hiasa S. (2015). Practical identificationof favorable time windows for infrared thermography forconcrete bridge evaluation. Constr Build Mater, 101, 1016–1030

Weaver J.M. (2011). Innovative Energy Harvesting Technology for Wireless Bridge Monitoring Systems. Ph.D. Dissertation. The University of Texas at Austin.

Wen L., Li X., Gao L. (2020). A transfer convolutional neural network for fault diagnosis based on ResNet-50. Neural Comput Appl 32:6111–6124. DOI: 10.1007/s00521-019-04097-w

Woldesenbet A. K. (2014). Highway infrastructure data and information integration and assessment framework: A data driven decision-making approach. Ph.D. Thesis. Iowa State University.

Wu C., Wu P., Wang J., Jiang R., Chen M., Wang X. (2022): Critical review of data-driven decision-making in bridge operation and maintenance, Structure and Infrastructure Engineering, 18 (1): 47–70. DOI: 10.1080/15732479.2020.1833946

Wu Q., Okabe Y., Yu F. (2018). Ultrasonic Structural Health Monitoring Using Fiber Bragg Grating. Sensors 18, 3395. DOI:10.3390/s18103395

Wu Z., Song S., Khosla A., Yu F., Zhang L., Tang X., Xiao, J. (2015). 3d shapenets: A deep representation for volumetric shapes. In Proceedings of the IEEE conference on computer vision and pattern recognition, 1912-1920.

Xia T., Yang J., Chen L. (2022). Automated semantic segmentation of bridge point cloud based on local descriptor and machine learning. Automation in Construction, 133, 103992.

Xing C., Wang P., Dong, W. (2020). Research on the bridge monitoring method of ground-based radar. Arabian Journal of Geosciences, 13(23): 1-10.

Xiong S., Wang C., Qin X., Zhang B., Li, Q. (2021). 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 Sensing, 13(4), 546. DOI: 10.3390/rs13040546

Yang G., Fan X., Wang S., Wang B., Liu Q, He Z. (2016). Long-Range Distributed Vibration Sensing Based on Phase Extraction From Phase-Sensitive OTDR. IEEE Photonics Journal, 8 (3). DOI: 10.1109/JPHOT.2016.2552820

Yang Y.B., Wang Z., Shi K., Xu H., Wu Y.T. (2020). State-of-the-Art of Vehicle-Based Methods for detecting Various Properties of Highway Bridges and Railway Tracks. International Journal of Structural Stability and Dynamics, 20 (13), 2041004. DOI: 10.1142/S02194554204100472041004-1

Yang S., Huang Y. (2021). Damage identification method of prestressed concrete beam bridge based on convolutional neural network. Neural Comput Appl 33:535–545. DOI: 10.1007/s00521-020-05052-w

Yao Y., Ellen S.T., Glisic B. (2014). Crack detection and characterization techniques—An overview. Struct. Control Health Monit., 21:1387–1413. DOI: 10.1002/stc.1655

Yao Y., Glisic B. (2015). Detection of Steel Fatigue Cracks with Strain Sensing Sheets Based on Large Area Electronics. Sensors, 15: 8088-8108. DOI: 10.3390/s150408088

Ye X.W., Dong C.Z., Liu T. (2016). A review of machine vision-based structural health monitoring: methodologies and applications. Sensors, 16, 7103039.15.

Zandi K., Ransom E. H., Topac T., Chen R., Beniwal S., Blomfors M., Chang F.K. (2019). A framework for digital twin of civil infrastructure - Challenges and opportunities. The 12th International Workshop on Structural Health Monitoring, Stanford, California, USA.

Zhang Y., O'Connor S. M., Van der Linden G. W., Prakash A., & Lynch J. P. (2016). SenStore: A scalable cyberinfrastructure platform for implementation of data-to-decision frameworks for infrastructure health management. Journal of Computing in Civil Engineering, 30(5), 04016012.DOI: 10.1061/(ASCE)CP.1943-5487.0000560

Zhou S., Sheng W., Deng F., Wu X., Fu Z. (2017). A Novel Passive Wireless Sensing Method for Concrete Chloride Ion Concentration Monitoring. Sensors 17, 2871. DOI: 10.3390/s17122871

Zhou G. D., Xie M. X., Yi T. H., Li H. N. (2019). Optimal wireless sensor network configuration for structural monitoring using automatic-learning firefly algorithm. Advances in Structural Engineering, 22(4): 907–918. DOI:10.1177/1369433218797074

Zhu J., Lu Z., Zhang C. (2022). A marker-free method for structural dynamic displacement measurement based on optical flow. Structure and Infrastructure Engineering, 18(1): 84-96. DOI: 10.1080/15732479.2020.1835999

Žnidarič A., Kreslin M., Anžlin A.,Krivic A. (2020). Detection of Delaminated and Cracked Concrete with Unmanned Aerial Vehicles, Routes/Roads, Vol. 386