Regional-scale bridge health monitoring: survey of current methods and roadmap for future opportunities under changing climate

Regional-scale bridge health monitoring: survey of current methods and roadmap for future opportunities under changing climate

Said Quqa[1], Othmane Lasri[2], Giulia Delo[3], Pier Francesco Giordano[2], Cecilia Surace[4], Alessandro Marzani[1] & Maria Pina Limongelli[2]*

[1] Department of Civil, Chemical, Environmental and Materials Engineering, University of Bologna, Viale del Risorgimento 2, 40136 Bologna, Italy

[2] Department of Architecture, Built Environment and Construction Engineering, Politecnico di Milano, Piazza Leonardo da Vinci 32, 20133 Milan, Italy

[3] Department of Mechanical and Aerospace Engineering, Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129 Turin, Italy

[4] Department of Structural, Geotechnical and Building Engineering, Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129 Turin, Italy

* Corresponding author. Email: said.quqa2@unibo.it

Abstract

Climate-related extreme events are becoming increasingly frequent, posing significant threats to bridges, which are critical components of transportation infrastructure. This paper offers an overview of recent advancements in methodologies and technologies for conducting structural health monitoring (SHM) of bridges over large areas, where deploying sensors on every structure may be cost-prohibitive for local administrations. It specifically examines two approaches that have garnered interest in the past decade: indirect SHM, which involves instrumenting vehicles and analyzing their dynamic responses to infer information about bridges, and satellite interferometric radar data, which offers static displacement measurements for large regions and has recently been exploited for civil SHM purposes. Additionally, it reviews the recent developments in population-based SHM, which facilitates knowledge sharing among structures with similar characteristics within a population. Through an analysis of the advantages and limitations of these three rapidly developing research areas, the paper outlines future opportunities and lays the roadmap for a comprehensive "regional-scale SHM" approach based on remote and/or crowdsourced data, supported by population-level analyses. Specific topics addressed include strategies for similarity assessment among monitored structures, available data sources, and feature extraction/integration approaches for different scenarios.

Keywords: population-based structural health monitoring, transfer learning, interferometric synthetic aperture radar, indirect structural health monitoring, drive-by, damage identification.

1. Introduction

Bridges are critical components of transportation networks, enabling crossing over natural and artificial obstacles while significantly cutting travel time. However, their indispensable function comes with inherent vulnerabilities, as bridges are susceptible to deterioration over time due to processes such as corrosion and fatigue, as well as specific events that include earthquakes, collisions, and landslides [1].

Recently, extreme climate-related events have become more frequent, underscoring the importance of preventing bridge failures which endanger human lives and result in substantial economic losses, primarily due to increased travel times [2]. Besides heightened risks from increased demand in structural performance, climate change exacerbates structural vulnerabilities through factors such as accelerated deterioration rates, higher sea levels for coastal structures, and scour induced by floods. Moreover, previously unexperienced environmental conditions make new data necessary to calibrate structural performance models and update design codes.

Accurate modeling of structural conditions and responses to various hazards requires extensive information, especially with the growing emphasis on methods to enhance the resilience of transportation networks [3,4].

Over the past three decades, structural health monitoring (SHM) has emerged as a valuable complement to traditional inspection practices in assessing the integrity of the transportation infrastructure [5]. SHM techniques typically involve the deployment of sensing devices directly onto bridges, including sensors, cables, and acquisition systems. They can capture a broad spectrum of data, from static quantities (e.g., displacements) to dynamic features (e.g., modal parameters), allowing for a comprehensive evaluation of bridge conditions. In the context of resilience management, decision makers can be supported by real-time SHM systems that provide continuous updates on bridge conditions [6] and integrate multiple types of data into digital twins [7].

Despite the potential of SHM systems for real-time monitoring and early anomaly detection, their widespread implementation presents practical challenges. First, the initial investment and ongoing maintenance required for deploying on-site SHM devices on a large scale can be prohibitive, especially for regional networks encompassing numerous bridges. Second, the traditional SHM approach typically involves examining the behavior of each structure individually, which typically requires collecting extensive datasets to distinguish among different structural conditions (e.g., due to environmental variations or deterioration phenomena). When dealing with large bridge networks, this results in massive data to process and store, further complicating the implementation of SHM at a network-wide scale. In addition, the effectiveness of SHM systems is impacted by climate change, as extreme environmental conditions (e.g., heatwaves), which are becoming more frequent, can increase the occurrence of false alarms. These extreme conditions were not as common in the past and were often not accounted for when calibrating damage identification algorithms designed to filter out environmental and operational effects [8].

Three recent approaches have emerged in the landscape of SHM for achieving widespread monitoring in a region of interest: (1) leveraging crowdsourced data collected by users using moving vehicles, (2) using remote sensing technologies installed onboard satellites, and (3) facilitating knowledge sharing among different structures through transfer learning strategies.

The first approach, also known as "indirect" or "drive-by" SHM (ISHM) [9], involves gathering information from sensors installed in moving vehicles, thus substantially reducing instrumentation costs for bridge managers. ISHM relies on mobile devices passing over several bridges in the region during user trips, with intervals of processed data selected while the vehicle is on the bridges of interest. Crowdsourced strategies have emerged recently, wherein drivers contribute data using their smartphones while crossing bridges [10]. This is a current and dynamic research area that has recently attracted significant research funding to explore synergies between Cooperative, Connected, and Automated Mobility (CCAM) and smart infrastructures for SHM [11].

The second approach employs satellite-based interferometric synthetic aperture radar (InSAR) data for bridge monitoring, eliminating the need for on-site sensor installation and maintenance [12]. Unlike ISHM, which typically focuses on identifying dynamic structural features, InSAR is primarily used for static monitoring. It provides velocity maps and time series of displacements, offering insights at both regional and local scales. Its non-intrusive nature allows for continuous monitoring without disrupting bridge operations, even in difficult environments. Additionally, it allows accessing historical data, thus providing information on past bridge behavior and facilitating trend analyses for proactive maintenance or studying bridge collapses occurred in the past.

The third approach, referred to as “population-based” SHM (PBSHM) in civil engineering [13], aims to enhance knowledge about certain elements in the monitored area (e.g., a network of structures or bridges with limited or unavailable data under specific conditions) by leveraging information from other structures. Successful knowledge transfer relies on ensuring that the bridges involved are sufficiently similar [14,15]. Various methods, typically imported from other research fields, have been proposed to assess similarity and facilitate knowledge transfer between bridges [14,16–18]. Given sufficient similarity, one typical application consists of extending labels of structural anomalies observed for some bridges to characterize other bridges in the monitored population.

Published reviews exist on recent trends in bridge SHM [19], PBSHM [20], ISHM [21], and remote SHM [22], which focus on highlighting current developments within each area and identifying potential improvements. Conversely, this paper examines specific aspects of these three fields with the primary objective of proposing a roadmap for their integration. To this aim, this study gathers and examines the latest significant advancements across the three aforementioned monitoring approaches, and outlines the data sources and methods that are already available to implement the proposed integration, while also highlighting what is still needed to maximize its effectiveness.

Structures in the same region are often built according to similar design specifications and are exposed to comparable loads and environmental factors, which are expected to evolve consistently with changing climate conditions. During extreme weather events, the availability of datasets from multiple structures under similar conditions might enhance the effectiveness and robustness of SHM. In such cases, the anomalous behavior observed across several bridges is more likely attributable to environmental factors rather than structural damage. Therefore, a novel approach is proposed to use regional-scale data for condition assessment of multiple bridges simultaneously.

Based on this rationale, guidelines to perform the basic steps of PBSHM (feature selection, similarity assessment, and knowledge transfer) are proposed in the perspective of using data collected through ISHM and satellite-based SHM. This approach leads to a novel PBSHM methodology, based on widely available data sources rather than on vibration data from on-site sensors, as seen in current applications. The key novelty of this approach is its scalability to the regional scale, while its main advantage consists in the limited cost. This aspect becomes particularly crucial for monitoring transportation networks that span across a territory, which is a typical case for management agencies.

The rest of the paper is organized into three sections of literature survey on ISHM, InSAR-based remote monitoring, and PBSHM. Each section is further organized in subsections analyzing the available data types and algorithms used in each approach, available benchmarks, and current challenges. Then, the proposed roadmap is presented, and the gaps that need to be addressed to implement it are identified. Conclusions are reported at the end.

2. Indirect structural health monitoring

The initial theoretical exploration of using moving vehicles with installed sensors was introduced by Yang et al. in 2004 [23], demonstrating the feasibility of this approach. Subsequent studies extended this concept, coining the term "indirect SHM" to distinguish it from traditional "direct SHM" methods employing contact sensors. Over the past two decades, a significant body of research has developed various ISHM techniques based on vibration data collected from moving vehicles. The underlying principle is that the dynamics of a vehicle traversing a bridge contain information about both the vehicle and the structure. By applying identification algorithms to the vehicle vibration response, both global and local features of the structure can be extracted, as the data collected over time also corresponds to spatial information as the vehicle moves (see Fig. 1). However, due to the high uncertainties inherent in this approach, statistical analyses based on multiple vehicle passages are often required.

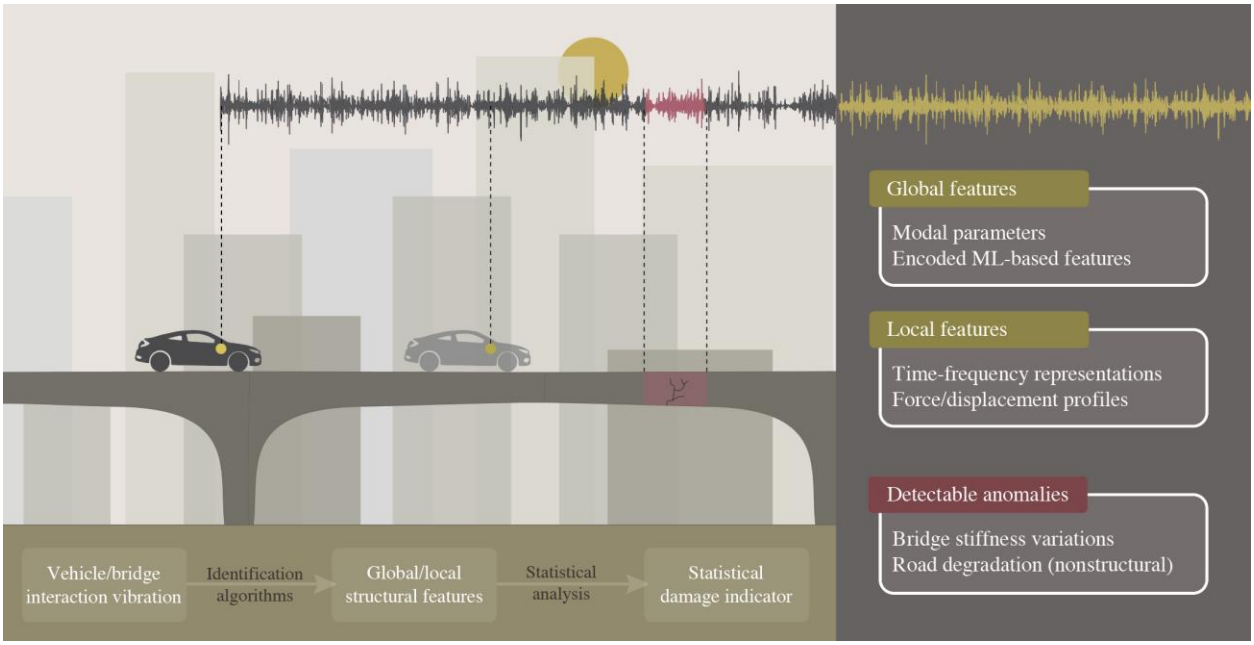

Fig. 1 – Scheme of the indirect structural health monitoring approach

Conventional algorithms employed in dynamic SHM often rely on stringent assumptions regarding the stationarity of structural response and a broad frequency spectrum of excitation sources. These assumptions are typically met when analyzing ambient vibrations, provided that the signal window considered in the analyses is sufficiently long. In ISHM methods, the signal collected while a vehicle traverses the bridge may be extremely short and heavily influenced by the dynamic characteristics of the vehicle. Studies have revealed that bridge frequencies change with the position of the vehicle and other mechanical properties due to vehicle-bridge interaction (VBI) phenomena [24]. Moreover, if the signal is collected onboard the vehicle, a substantial portion of the dynamic response reflects the vehicle properties, which is not informative for SHM.

While ISHM contradicts fundamental assumptions of operational modal analysis (OMA), Locke et al. [25] explored the possibility of using conventional OMA techniques in ISHM for identification of modal parameters on a short bridge. Different techniques were assessed, revealing that frequency domain methods proved generally more accurate in detecting higher-order frequencies. Conversely, time-domain methods minimized the detection of spurious modes and provided a distinct identification of the fundamental bridge frequency.

In addition to concerns regarding applicability of the identification methods, some scholars have explored the impact of traffic loads on the identified parameters. Sitton et al. [26] established closed-form solutions for the vibration of a two-span continuous bridge traveled by a vehicle and a method to identify bridge frequencies from vehicle response. The results indicate that the bridge frequencies observed by the vehicle appear as two peaks shifted below and above the fundamental bridge frequency due to the time-varying configuration of coupled masses and stiffnesses. In general, the average of these frequencies approximates the actual bridge frequency with an acceptable error, which decreases when the bridge spans have similar lengths. May [27] investigated the impact of operational traffic variability on the results of ISHM. The research shows that traffic conditions leading to an increase in the vehicles-to-bridge mass ratio may introduce variations in the bridge modal frequencies comparable to damage. Furthermore, relatively high traffic densities may not ensure the steady-state conditions required in usual identification methods due to varying traffic speed and vehicle spacing. This variability can further impact the identified modal frequencies. Some authors [28,29] observed that expansion joints induce bounce and pitch motions in vehicles, and their prevalence in the vehicle dynamic response can hide the bridge response. The authors suggested to remove the affected part of the collected signal from the analyses, thus further reducing the length of the processed signal.

Although these concerns carry less significance in railway bridges, given the consistent speed of train passages, other challenges arise from the high velocity of the vehicles and the periodic nature of the loading function. Reiterer et al. [30] investigated the impact of accelerometer placement on a passing train, examining positions on the bogie or train body to identify the optimal location for enhancing the visibility of the first vibration mode of the bridge. The study found that the bogie frame provides more accurate results, with considerable influence from the train suspensions on the response spectrum.

Given the difficulties of applying identification strategies originally developed for OMA in ISHM, several authors have proposed innovative methods explicitly addressing the issues associated with the moving sensors and their induced effects. Gkoumas et al. [31] provided a comprehensive review of available ISHM solutions, including technologies and methods proposed until 2020. Also, Gkoumas et al. [11] discussed the policy enablers and bottlenecks for utilizing CCAM in ISHM of transport infrastructure. Moreover, Shokravi et al. [9] conducted a comprehensive review of ISHM studies conducted before 2020, surveying various approaches such as vision-based, weight-in-motion, drive-by, and VBI.

The primary contributions in this field with a predominant focus on recent years are surveyed in the following, aiming to assess the readiness level of this research branch and identify the necessary requirements to enable practical applications for regional-scale SHM.

2.1 ISHM data and algorithms

The first methods employed in ISHM consisted of using traditional OMA methods to identify modal parameters from indirect measures. Yang et al. [23] conducted the first study on the feasibility of extracting bridge frequencies from the dynamic response of a passing vehicle using the fast Fourier transform (FFT). Some years later, Cerda et al. [32] used wireless sensors on a lab-scale model for the same purpose. In addition to natural frequencies, some authors explored the identification of other modal parameters, namely damping, through indirect measures. Keenahan et al. [33] proposed using a truck-trailer vehicle system, employing accelerometers on the trailer axles to identify damping and its variations associated with damage, modeled as a loss in stiffness of the bridge.

In initial works, detecting variations of modal parameters potentially due to damage proved challenging due to the low frequency resolution of the Fourier transform [34]. Li et al. [35] were among the pioneers in introducing a method using a generalized pattern search optimization algorithm to identify parameters for the vehicle–bridge system, such as bridge stiffness and its first frequency, through model fitting, thereby offering an alternative to relying solely on the interpretation of the frequency spectrum. The method demonstrated notable robustness, especially in the presence of noise.

Between 2015 and 2020, methods accounting for time dependence of the collected signal were developed. Specific techniques based on the wavelet transform, Hilbert transform, and other methods to deal with non-stationary signals were introduced to handle short time histories, a topic still under study today. Tan et al. [34] employed wavelet analysis to identify natural frequencies from indirect measures. Building upon the methodology introduced by Keenahan et al. [33], this study also explored the use of a subtracted signal from two consecutive axles to effectively eliminate the impact of road roughness from the recorded acceleration history. In subsequent work, Tan et al. [36] introduced an algorithm to extract bridge mode shapes and damping ratios using indirect acceleration measures, leveraging the Hilbert transform and accounting for VBI effects. Moreover, Tan et al. [37] proposed a method based on the entropy of wavelet components extracted from the signal to identify discontinuities indicative of damage, thus providing an estimate on its location and extent.

Entering the realm of crowdsourcing, which is particularly animated today with the prevalence of shared vehicles [38,39], Eshkevari et al. [40] introduced a method to identify natural frequencies and the absolute values of operational mode shapes with high spatial resolution. They employed the wavelet transform on asynchronous signals gathered by multiple vehicles, averaging the results to eliminate sources of noise and vehicle dynamics. By incorporating data from different lanes of the bridge, the method allows the reconstruction of 3D mode shapes. McGetrick et al. [41] compared smartphones and wired sensors installed in vehicles, showing that smartphones also embed global navigation satellite system (GNSS) receivers for recording the vehicle position in the transportation network.

Nevertheless, the authors emphasized the challenges associated with identifying bridge parameters using both systems. A few years later, Quqa et al. [38] employed a crowdsourced approach with stiff shared bikes to identify the first natural frequency and absolute value of the corresponding mode shape. This was achieved leveraging fusion of inertial measurement unit (IMU) data through a Kalman filter. Notably, the study considered scenarios where the vehicle has random velocities. Matarazzo et al. [39] proposed a method involving smartphone data collected from Uber rides. The authors conducted tests on different structures, including a long-span suspension bridge in the USA (the Golden Gate Bridge) and a bridge in Italy, employing different smartphone and car models. O'Brien et al. [42] recently conducted a statistical study on the scalograms obtained from the passage of multiple vehicles on a bridge to identify and localize anomalies indicative of scour damage.

Besides time information relevant to the vehicle position, some recent trends exploit the high resolution of time-frequency representations of the signal to investigate complex phenomena in the VBI. For instance, Tan et al. [43] introduced a nonlinear time–frequency analysis approach to investigate the time-varying frequencies in the VBI system using the second-order synchrosqueezing transform. Given the time-varying characteristics of VBI, the frequencies of both vehicles and bridges exhibit variations over time. Their findings emphasize the necessity to differentiate the extracted drive-by bridge frequency from that obtained through direct measurements, aligning with previous studies [24,26–29], and underscore that VBI effects should not be generally overlooked.

Addressing VBI effects through data-driven methods presents inherent challenges. Consequently, a substantial portion of recent research has been dedicated to model-based approaches. Elhattab et al. [44] introduced a monitoring system using trucks equipped with accelerometers. By calculating the "apparent" profile through VBI modeling and analyzing the difference before and after damage, the approach proves effective for damage localization. The approach was used to identify local damage in a 2D plate bending bridge model, showing that the damage is more visible if the vehicle passes close to the damage location. Li et al. [45] presented a two-step method for damage detection. After estimating the road surface roughness from the dynamic responses of a passing vehicle using the dual Kalman filter, bridge damage was identified based on interaction force sensitivity analysis with Tikhonov regularization. Corbally and Malekjafarian [46] extracted the response at the contact point between the bridge and tire using an analytical VBI model and suspension characteristics. This response was then used for frequency identification, outperforming methods relying on recordings collected on the vehicle body. The paper also discussed the limitations of conventional vehicle-bridge interaction modeling that considers a single contact point directly below the center of the wheel. The proposed method adopted a rigid-disk model to address these shortcomings. To further improve robustness to noise, Mokalled et al. [47] proposed a Bayesian estimation technique to analyze vehicle data and update a physics-based vehicle–bridge finite element model (FEM) for detecting, localizing, and provide information on the entity of crack damage.

While models can effectively capture complex dynamic effects, their success relies on possessing comprehensive knowledge of both the structure and the vehicle. In the absence of such knowledge, many researchers used machine learning methods to infer missing information from the available data. This avenue of research has garnered significant interest, particularly since 2020. Locke et al. [48] proposed using convolutional neural networks on the FFT of the acceleration response of passing vehicles to standardize the length of the acquired signal for automatic usability and reduce the dimensionality of the input. Hesser et al. [49] used the frequency response of train responses to identify damage as well. They used an artificial neural network (ANN)-based approach to identify the train position through IMU measures and discarded outliers in the vehicle response through autoencoders to limit false alarms. Liu et al. [50] explored the relationship between damage and changes in acceleration responses using more advanced dimensionality reduction methods. The most representative features of the structural response were employed for damage identification through semi-supervised learning. The researchers observed nonlinear relations and found that both the low- and high-frequency component of vehicle response may carry information about damage severity, as confirmed by Li et al. [51] a few years later. In this last study, Mel-frequency cepstral coefficients derived from the frequency responses of recorded accelerations, originally applied in acoustic recognition, were used for damage classification along with support vector machine (SVM). Frequency responses were also at the base of the method proposed by Li et al. [52], who used the reconstruction error of autoencoders as a damage-sensitive feature. With a similar rationale, Calderon Hurtado et al. [53] proposed an unsupervised learning framework using adversarial autoencoder for detection of damage on simply supported beam-like bridges. This method requires the same test vehicle to be regularly used for

bridge inspection, passing with a constant and low speed. These limits on vehicle speed are popular in other works [54,55]. On the other hand, relying on a time-frequency representation of the collected vehicle response, Hajializadeh [56] used 2D CNNs to detect damage from spectrograms of acceleration signals collected on instrumented trains. The hyperparameters of the algorithm were optimized using Bayesian optimization techniques.

2.2 ISHM identification level

While the ultimate goal of SHM is to detect changes in structural behavior potentially associated with damage, the structural parameters extracted from data can also serve broader purposes such as model updating and enhancing overall structural knowledge. Assessing the condition of roads is another widely explored field. However, this paper will not address it due to its non-structural nature.

Among the surveyed studies, many methods were used to identify modal parameters and, in the majority of the cases, the first natural frequencies of the bridges. In such cases, the main challenges were related to the short signals collected on board the travelling vehicles, resulting in a frequency spectrum with low resolution [33,34]. Issues such as frequency shifts due to load variability [24,26–29], and the presence of vehicle dynamics in the response, which can mask the dynamic behavior of the bridge [46] were also encountered. Significant research has been devoted to these issues, finding the main solutions in time-frequency representations of the signal and explicit VBI modeling. The former approach has also shown promising in some studies to identify mode shapes [34,40]. Conversely, the explicit VBI formulation has been successfully employed to identify the bridge damping ratio [33,34].

Methods that addressed the problem of damage identification predominantly focus on damage detection, especially those grounded in machine learning. Some of these methods also attempt to quantify the extent of damage. This finds a justification in the fact that conventional machine learning tools facilitate classification into predetermined classes that are not well suited with the localization problem. For instance, studies have shown that the reconstruction error of autoencoders generally increases with damage [50,52,53]. However, reconstruction accuracy can also be influenced by other factors [49]. In reality, given the absence of information about the specific type of damage and the nonlinear relationship between damage "intensity" and reconstruction error, the concept of "damage quantification" should be carefully interpreted. Other classification methods [48,51,55,56] necessitate the prior determination of damage classes (and extensions), making them challenging for real-world applications due to their case-dependent nature. Moreover, potential unaccounted variations in the data may lead to incorrect results. Alternatively, unsupervised machine learning methods have demonstrated the ability to differentiate between various damage states through clustering [54]. While this approach requires human intervention to assign label names to the clusters and link them to real conditions, it holds promise for widespread applications, contributing to the reduction of visual inspections only when data anomalies are detected.

When the type of damage is assumed to be of a known type (e.g., local stiffness variations), some methods [37,47] showed ability to identify its position and, in some measure, its extension. Methods enabling damage localization often rely on VBI models or time-frequency representations of structural responses, linking the time intervals of detected anomalies to the position of the moving vehicle. In this context, variations in the displacement profiles measured onboard the vehicles or reconstructed through VBI models before and after a damaging event can be used to localize the structural defect [44,57]. Moreover, local anomalies have been found to vary locally the energy [42,56] or entropy [37] of wavelet components. Notably, these approaches typically demand detailed information on vehicle position or strict assumptions regarding vehicle speed. In the cases where such information is required, IMU measures available on standard smartphones has proven to be highly beneficial [38,39].

2.3 ISHM bridge benchmarks

The validation of methodologies proposed in the field of ISHM is predominantly conducted on simulated and laboratory models. This can be attributed to the fact that obtaining permissions to conduct tests on a real bridge impacted by known structural issues is often denied by managers, who may also prohibit traffic for safety reasons. However, testing the proposed methods on realistic numerical simulations or laboratory-scale models is essential to assess their applicability and limitations.

In studies on ISHM, numerical simulations typically assume the damage as a local stiffness reduction (either as a reduction of the cross-section size [37,44,48,53], elasticity modulus of the material [54], or more advanced models based on the theory of fracture mechanics [47]). This type of damage can be attributed to spalling and cracking in reinforced concrete bridges, or corrosion and connection issues (e.g., bolt loosening) in steel bridges and truss structures.

Laboratory-scale models are also very popular among the research community in this field. Most of them model variations in the mechanical properties of the structure as concentrated additional masses, owing to the simplicity and reversibility of such variations [50,51,53,55,56,58]. Nevertheless, alternative strategies have also been explored, including the integration of local stiffeners [54] and the use of different dampers [36].

While the number of real case studies remains limited, certain methods have been applied to identify the dynamic properties of bridges in these scenarios, albeit without explicitly considering variations attributed to damage.

Initially, McGetrick et al. [41] acknowledged the limitations of instrumented vehicles traversing bridges for a very brief period of time and with a relatively small weight compared to that of the structure. In this case, the vehicle cannot be considered an effective exciter, and the analyses should be done considering ambient vibration. In contrast, studies focused on train responses, which typically present less variability (e.g., almost constant speed and fixed path) and induce considerable bridge excitation, presented notable results. For instance, Reiterer et al. [30] successfully identified the first frequencies of an Austrian railway bridge using an instrumented train.

Pedestrian bridges, relatively easy to excite through activities such as running, walking, or nearby traffic, also yielded promising findings. Quqa et al. [38] identified the frequencies and absolute values of mode shapes of a pedestrian bridge in Bologna, Italy using instrumented bicycles. The authors exploited the relatively high stiffness and absence of dampers in the bikes to uncouple bridge and vehicle dynamics. In this case, smartphones installed on the bicycles provided usable data.

Notable results in terms of modal parameter identification were also achieved with cars instrumented with smartphones in the case of long and flexible suspended bridges. Matarazzo et al. [39] tested various cars equipped with different smartphone models identifying the main resonant frequency from multiple passages on the Golden Gate bridge, in USA. The authors conducted similar tests on a shorter (28m long) reinforced concrete bridge in Italy, passing over it more than 250 times, and successfully identifying its first frequency without explicitly modeling any VBI effects. It is noteworthy that the shorter the bridge, the more challenging the identification task. Locke et al. [25] identified the main frequency of an 18m long reinforced concrete bridge near Greenwood, in South Carolina (USA), using a car equipped with multiple accelerometers. To mitigate high noise and short signals (each vehicle passage lasting less than 3 seconds), they conducted separate analyses of the front and rear wheel response data and strategically positioned sensors on the unsprung masses of the vehicle.

In one of the rare case studies involving real damage, Hesser et al. [49] evaluated the health status of a suspension railway (i.e., the Skytrain in Düsseldorf – Germany). The tests were performed after removal of one bolt in a structural connection. Safety measures were implemented to ensure that no passengers were on board during the tests.

Conducting tests on field datasets is crucial to address conditions often overlooked in simulations. Factors such as road roughness, typically considered in numerical models, may be unrealistic in a laboratory setting. Additionally, the bridge cross-section and support conditions in both numerical and laboratory models often deviate from reality. Other differences between real tests and simulated conditions regard the loading conditions. For instance, the eccentricity of the load due to lane positions is rarely considered in simulations [44], as well as the presence of multiple loads at various and non-uniform speeds, and the influence of other sources of excitation (e.g., wind or nearby traffic). Although some studies consider the effects of environmental conditions (e.g., temperature [48]) on the mechanical properties of the structure, their impact on boundary conditions is usually neglected. Here, inherent nonlinearities of real support devices may induce unconsidered effects in the bridge response.

Furthermore, real damage may affect different parts of the structure, producing concomitant effects. While changes in stiffness are the ones most investigated in simulated models, they may become apparent only when the structure has already experienced an advanced level of damage in reality.

2.4 Current challenges in ISHM

The ISHM methods reviewed in this paper predominantly focus on modal parameters or measured/reconstructed displacement profiles. However, variations in dynamic parameters and deflections induced by moving loads primarily stem from changes in the structural stiffness. Movements of supports due to settlements or scour do not significantly affect the dynamic behavior of statically determinate structures. Therefore, this limitation restricts the applicability of current drive-by damage identification methods to specific damage types and use cases.

Moreover, the typically high noise level of indirect measurements implies that stiffness alterations may only be detectable when extensive datasets are available. Even in this case, variations in identified parameters may be due to varying masses (i.e., traffic conditions) and VBI effects. This underscores the need for effective crowdsensing strategies and statistical analyses of the varying structural parameters.

Another challenge lies in determining a damage-sensitive feature that can be computed, along with its statistical description, for data recorded from different vehicles. Since OMA is not directly applicable to the typically short signal time histories obtained in ISHM, non-stationary phenomena cannot be neglected. Additionally, each vehicle passage is unique due to the vehicle characteristics, recording duration, and specific travel path, thus producing inconsistent datasets that need standardization.

Despite several studies validating ISHM methods in current literature, most of them rely on simulated structures or laboratory models. Extensive field validation is lacking, particularly for crowdsourcing strategies.

3. Synthetic aperture radar interferometry

Different from ISHM, which relies on identification of dynamic structural features, InSAR techniques have been gaining attention to conduct static monitoring. InSAR methods are based on the synthetic aperture radar (SAR) technology aboard orbiting satellites, delivering weather-independent imagery of the Earth surface. Various natural and man-made structures (such as rocks, house roofs, and road surfaces) strongly reflect the electromagnetic signals emitted by SAR sensors. These sensors receive the signals, creating radar images of the Earth surface—commonly known as SAR images. A SAR image is a matrix where each cell (or pixel) corresponds to a complex number which represents radar echo information, related to the land coverture within the pixel. This information relies on different aspects of the scene captured by the SAR image; especially, the radar echo phase is influenced by the target-satellite distance while the amplitude is mainly influenced by the acquisition geometry, the technical parameters of the sensor, and the surface roughness and orientation. InSAR techniques compare at least two images acquired by the satellite over the same area at different times to generate a matrix, also known as an interferogram, where each pixel provides information on the phase difference recorded between the two images. Assuming that the distance traveled by the emitted/backscattered signal can be expressed as a non-integer number of wavelengths ($n\lambda + \Delta\lambda$), the phase difference is reconstructed from the fractional part $\Delta\lambda$. **Error! Reference source not found.** shows a graphic representation of how SAR satellites can measure bridge displacements.

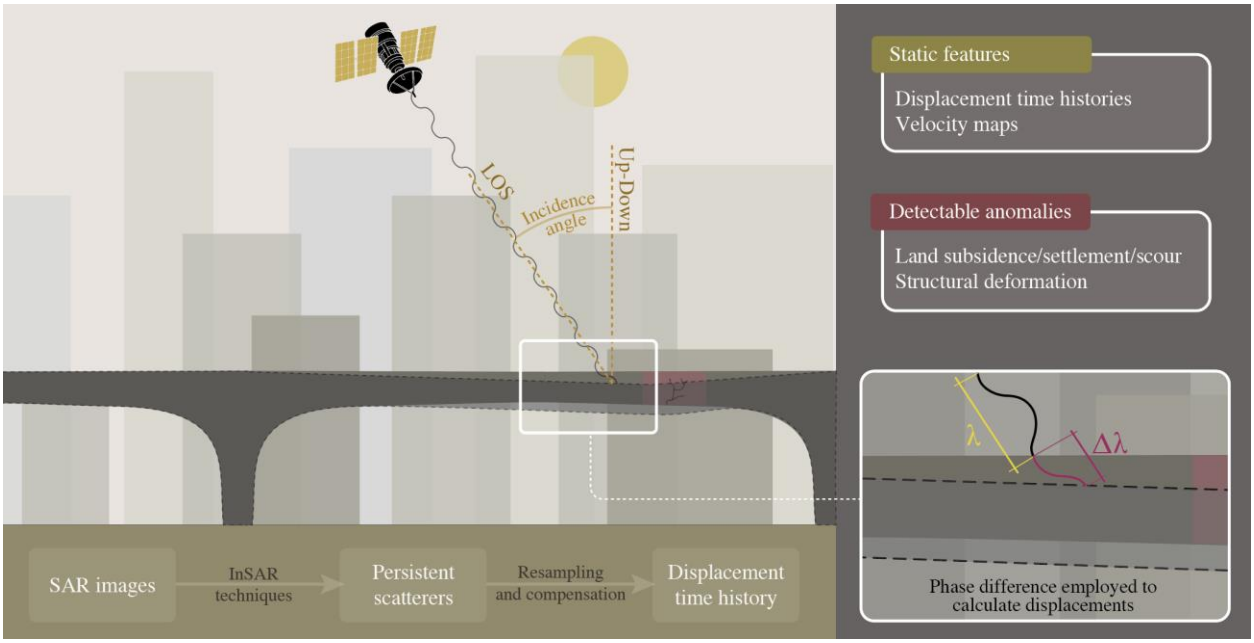

Fig. 2 – Scheme of the satellite-based monitoring approach

In an ideal case, if the wavelength λ is known, the phase difference can be directly used to estimate the displacement value in each pixel [59,60] along the line of sight (LOS) that connects the SAR sensor to the pixel area. However, phase variations can also be induced by operational noise and different acquisition conditions of the two images [61].

The displacement estimated along the LOS is a projection of the real ground displacement. When the target is not parallel to the LOS direction, interpreting the real ground displacement can be challenging. The redundancy of views acquired by different satellite orbits can be exploited to overcome this limit. An example is the derivation of the vertical (up-down) and horizontal (east-west) components of deformation using different orbit datasets is shown by Wright et al. [62].

Another important aspect is that not all ground areas reflect electromagnetic signals equally. The reflective object that dominates the radar response in the pixel, referred to as persistent scatterers (PSs), determines the regions at which the displacement data can be effectively estimated. The displacements of PSs can potentially achieve submillimeter precision depending on the methods used to process SAR images [63]. Some authors have compared local measurements obtained by on-site extensometers and InSAR data, confirming the accuracy of this approach [64].

The differential InSAR (DInSAR) technique [65] is one of the most used techniques to estimate displacements by exploiting the phase difference between two SAR images acquired by the satellite over the same area at different times. DInSAR is a well-established monitoring method in geoscience fields and enables the study of geophysical processes in glaciology [66], seismology [67], and volcanology [68]. A major limitation of DInSAR, which is based on the analysis of individual interferograms, consists of the errors due to inaccuracies in orbital information and variations in atmospheric conditions between acquisitions, which require reliable atmospheric models. To overcome its limitations, the interest of the scientific community has increasingly focused on the development of advanced multi-temporal DInSAR (MT-InSAR) techniques, capable of providing accurate information on the spatial distribution and temporal evolution of surface displacements that occurred in the area of interest during a certain period, through the generation of displacement time histories and maps of average ground velocity [63,69]. Despite the considerable algorithmic complexity and significantly longer computation times compared to classical interferometric techniques (analysis of a single/few interferograms), the information obtained in multi-temporal approaches using a large number of images and interferograms leads to a significant improvement in the accuracy of displacement measurements, which become also suitable for SHM.

Since 2006, the advent of the second generation of space-based SAR missions, such as the advanced land observing satellite (ALOS-1), TerraSAR-X (TSX), COSMO-SkyMed (CSK), and Sentinel-1A/B (SNT), has notably enhanced spatial resolution to the order of meters and temporal resolution to a few days. These advancements have significantly increased the density of PSs extracted from high-resolution SAR data compared to previous medium-resolution SAR platforms like RADARSAT and ERS or its successor Envisat (ENV) [70].

Recenlty, the European Space Agency (ESA) introduced the European Ground Motion Service (EGMS) as part of the Copernicus program, marking a notable advancement in satellite-based monitoring [71]. Commencing operations in 2022, EGMS uses data from Sentinel-1 satellites dating back to 2015, employing advanced InSAR techniques for analysis. It provides regular updates, on an annual basis. Accessible through a dedicated portal, EGMS offers user-friendly services, and a range of products customized to meet diverse user requirements. Notably, all services provided by EGMS are offered free of charge. EGMS uses the most consolidate MT-InSAR procedures (specifically, the PS-InSAR method, see Section 3.1) [61,72]. Moreover, a GNSS high-quality 50 km grid model is developed within EGMS, to calibrate the InSAR ground motion products. Downloadable products encompass InSAR measurements of ground motion along the LOS of the S1 satellite in ascending and descending geometries (level L2a), as well as calibrated products using a large scale GNSS velocity model (level L2b). The EGMS also provides ortho products (level L3) concerning vertical and east-west ground motion measurements, derived from multiple L2b products with complementary acquisition geometries [71].

3.1 InSAR data and algorithms

A key aspect in MT-InSAR analysis consists of selecting the appropriate SAR image type and InSAR algorithm, which in turn depends on the specific requirements of the application. SAR images are available in various frequency bands of the microwave spectrum, with each band offering different characteristics in terms of spatial resolution, penetration capability, and sensitivity to environmental conditions.

Two common bands used in SAR imaging are C-band and X-band [73]. C-band SAR images have a lower spatial resolution compared to X-band images. However, they offer better penetration through vegetation and are less affected by adverse weather conditions. These characteristics make C-band SAR suitable for applications including land cover classification, agriculture monitoring, and wide-area surveillance. Additionally, C-band SAR images are often freely accessible through various satellite missions, like Sentinel-1A/B. On the other hand, X-band SAR images (e.g. CSK images) provide higher spatial resolution compared to C-band images. This increased spatial resolution allows for capturing finer details in the imagery, making X-band SAR more suitable for monitoring individual structures. For the same study area, using a higher spatial resolution image means that the structure is captured by more pixels, potentially detecting more detailed displacement patterns. However, acquiring high-resolution imagery typically comes with higher costs (both economic and computational) compared to lower resolution options [74].

Among the scientific papers focusing on bridge monitoring, the majority used X-band SAR images (e.g., [75–78]). On the other hand, few studies are currently based on low spatial resolution data. An example is provided by Hoppe et al. [78]; the authors use Sentinel-1 images in a SBAS chain for assessing the Ganjiang Bridge displacements due to operational conditions and environmental effects. Nevertheless, Eskandari et al. [79] conducted a comparative study between CSK products and the PSs provided by EGMS, showing that both can be suitable for SHM and condition assessment of bridges. Furthermore, some authors processed data from different SAR satellites to exploit different bands and time resolutions [70,80–91]. An example is provided by Millillo et al. [83]; the authors used data from COSMO-SkyMed, Sentinel-1A/B, and Envisat, to study the deformation state of the Morandi Bridge over the Polsevilla River 15 years before its collapse. The authors showed that using the data from different satellite missions can complementarily enhance bridge displacement interpretability.

MT-InSAR algorithms can be mainly divided into three categories: single-master algorithms, multi-master algorithms and hybrid methods. The single-master algorithms choose the optimal reference image (master) and calculate phase differences by comparing this image with the remaining images (slaves). Multi-master algorithms select sub-stacks of images. For each sub-stack, a master image is selected, and the phase differences are calculated by comparing this master image with the remaining images (slaves) of the sub-stack. A few studies have employed hybrid approaches, which use both single and multi-master selection procedures [92,93].

Permanent scatterer interferometry (PS-InSAR) represents a special class of single-master algorithms [63,94]. The first pioneer work based on PS-InSAR was proposed by Ferretti et al. [61], followed by an extension, called SqueeSAR [72]. Hooper et al. [95] presented an important contribution in the field of PS-InSAR, proposing a novel PS selection approach based on phase characteristics. This work originated one of the most widely used MT-InSAR software packages, the Stanford method for persistent scatterers (StaMPS).

In single-master procedures, the master selection plays a key role in the outcomes, as assessed by several studies [60,61,96,97]. First MT-InSAR applications operated choosing the master image minimizing the spatial and temporal baseline between all interferometric pairs [98,99]. However, when the number of candidate images is big, the procedure becomes time-consuming. Hua Zhang et al. [100] proposed a mathematical model to overcome these limitations by solving an optimization problem in which temporal and spatial baselines are integrated together. As an alternative, Lu et al. [101] proposed a method to select the optimal master by using the sum of temporal baselines, spatial baselines, and Doppler centroid [102] frequency differences as a reference. The persistent scatterer pairs (PSP)-InSAR method mitigates issues related to atmospheric and orbital effects when identifying PSs. This approach increases PS density by leveraging the fact that pairs of closely spaced points are subject to the same disturbance [103,104].

Multi-master algorithms combine differential interferograms produced by image pairs with small orbital differences. Bernardino et al. [105] provided a seminal contribution to multi-master procedures by proposing the small baseline subset (SBAS) algorithm. Several extensions of the SBAS algorithm followed in subsequent years [60,106]. Compared to single-master procedures, SBAS algorithms are more suitable for automated methods. For instance, Lanari et al. [107] developed automated cloud computing procedures that leverage parallel processing, eliminating the need for new stack analysis when a new image becomes available, unlike single-master procedures. Similarly, Lazecký et al. [108] proposed a procedure to continuously monitor deforming regions using cloud storage and SBAS processing.

A common drawback of both the PS-InSAR and SBAS methods is the requirement for phase unwrapping, which is often time-consuming and error-prone. The temporal coherent point (TCP) algorithm, a multi-master technique, addresses this issue by using points in the interferograms that remain coherent over one or several intervals of SAR acquisitions, without needing to be visible throughout the entire observation period. This algorithm can identify PSs with a limited number of SAR acquisitions and estimate surface displacement without requiring phase unwrapping [89,109].

The coherent pixels technique (CPT-InSAR) is an algorithm that combines the linear model deformation and topographical phase error correction found in PS-InSAR with a multi-master comparison typical of an SBAS approach [110–112]. This algorithm becomes particularly beneficial when the stack of images covers a short time period, where traditional PS-InSAR and SBAS methods may struggle to maintain accuracy. Pastor et al. used a CPT-InSAR algorithm to monitor a bridge affected by a landslide [113]. More recently, Dong et al. proposed an improved version of the CPT-InSAR algorithm that increases the density of measurable points in vegetated areas [114].

Another pivotal aspect in MT-InSAR processing is the selection of the digital elevation model (DEM) used to estimate the topographical phase error [59,61]. Bayer et al. [115] analyzed the influence of the DEM on MT-InSAR outcomes by processing different stacks of SAR images using PS-InSAR and SBAS algorithms and comparing four DEMs (SRTM, ASTER, RDEM, and NDEM) [115]. They found that X-band data appeared more sensitive to small DEM errors, likely due to the large perpendicular baselines of the dataset and the short wavelength of the signal. The number of selected PSs varied by about 3% for C-band and 6% for X-band, depending on the DEM used. However, the 30-meter SRTM DEM generally provided a high number of PSs using both PS-InSAR and SBAS procedures. This suggests that a high number of SAR acquisitions and interferograms improves the estimation of topographical error. Conversely, datasets with low variance in perpendicular baselines (e.g., drifting baselines) or few observations reduce the quality of this estimate. The results underscored the importance of including the heights of houses, structures, and vegetation as imaged by the SAR data. Du et al. [116] confirmed that DEM accuracy has a greater influence on X-band data compared to L and C-bands, and that the SRTM provided the most reliable results in all analyzed cases.

PSs may also suffer from issues due to the instability of the environment, such as due to snow or scene variations (e.g., in building sites). Xu et al. [117] proposed a method to optimize the identification of PSs by improving the processing chain combining amplitude dispersion index and temporal coherence coefficient. Other authors addressed these shortcomings by exploring the integration of MT-InSAR with other SHM technologies [118,119]. Moreover, clustering methods have been employed to facilitate interpretation of the structural behavior, mimicking displacement sensors [120–122].

3.2 InSAR bridge benchmarks

In the context of bridge monitoring, InSAR data has been used to study deformations due to environmental factors and assessing abnormal displacements of the supports and abutments. Specifically, most contributions in the literature focus on analyzing the operational deformations of bridges caused by seasonal thermal effects, which exhibit a fluctuating pattern with a yearly cycle [80,84,123]. The prevalence of studies addressing temperature-related deformations is partly due to a scarcity of documented cases of structural damage. Moreover, some studies investigated bridge displacements induced by other natural phenomena (e.g., landslides [75,124], sediment consolidation [76,82,88,125], and scour [12,126]).

Depending on SAR images availability, historical images can be employed to retrospectively examine structures, even those that were not previously monitored [83,127–129]. This advantage makes also possible forensic investigations on collapsed bridges. For instance, Farneti et al. [128] investigated the pre-collapse data of the Albiano-Magra Bridge in Italy, which collapsed on 8 April 2020. The results, pertaining to the monitoring period of 2015–2020, demonstrate the effectiveness of InSAR in supporting engineering assessments, highlighting displacements of increasing amplitude in two side spans during the three years preceding the failure, and providing information on the possible cause of the collapse. Moreover, Selvakumaran et al. [12] processed 48 COSMO-SkyMed scenes over the Tadcaster Bridge (England), highlighting the reliability of InSAR to distinct movement in the region of the bridge where the collapse occurred prior due to the scouring action. The paper showed that partial collapse on the upstream side of a bridge could be predicted within a month by an automated outlier identification procedure. Entezami et al. [129] analyzed the same case study using an unsupervised machine learning method. Hoppe et al. [78] used InSAR data for studying permanent deformations of two posttensioned bridges in Virginia, finding the effects of extensive cracking in the concrete girders.

The primary challenge arisen with using InSAR data for SHM of bridges resides in the interpretability of the data. While it may be reasonable to justify anomalous events post-collapse, establishing a direct correlation between displacement trends and anomalies is not straightforward. This difficulty arises because InSAR data represent displacements along the LOS of the satellite are heavily influenced by bridge orientation. Consequently, there is no standardized approach to interpreting data trends for structural health assessment, leading to varying interpretations, as evidenced by recent analyses of the Morandi bridge pre-collapse behavior, which have generated conflicting viewpoints [83,130,131]. An effort to support the objective interpretation of MT-InSAR results has been made by the Italian Network of University Laboratories of Seismic Engineering (Reluis). They recently issued guidelines on the use of interferometric data for infrastructure monitoring, providing explanations on methodologies, technical details, and case studies [132].

Furthermore, the lack of sufficient persistent PSs across a bridge can exacerbate the complexity of data interpretation. Adding to the complexity is the uncertainty regarding the exact location of PSs on the structure [133]. Nevertheless, this issue can be addressed by deploying artificial corner reflectors. These devices, installed on-site, generate a robust response in SAR images resulting in good interferometric phases to derive the displacements. For instance, Kelevitz et al. [134] analyzed the L-band dataset over corner reflectors of various sizes showing how these in-situ installations can substantially enhance the quality of MT-InSAR results. Sadeghi et al. [86] used X-band images in the area of the Waterloo bridge to prove that installing corner reflectors, specifically oriented in the LOS of the selected satellites, increases the bridge signal in the SAR image significantly and facilitates the selection of PS at the desired locations.

To further enhance the interpretability of results, recent methods have incorporated structural models, such as finite element models (FEMs), simplified rigid models, and applied element method (AEM) analyses to have a prior estimate of the expected displacement patterns due to different phenomena. For instance, Farneti et al. [128] used AEM

analyses to identify displacement patterns related to potential anomalous mechanisms and exclude inadmissible ones. Additionally, Quqa et al. [135] developed simplified models for various types of expected anomalies and used synthetic data to train a classifier for real InSAR data, leveraging domain adaptation algorithms (see Section 4 for more details on these methods).

3.3 Current challenges in InSAR for SHM

In the context of bridge monitoring, the main limitations of SAR technology are related to the availability and position of PSs. The number and position of measurable points on the bridge cannot be predetermined and depend on various factors, including processing algorithm [136], image types, bridge orientation [137], weather conditions [138], and in situ operations [22]. The inconsistent data availability also results in variable spatial distribution of PSs from different orbits and asynchronous displacement time histories.

To address this challenge, spatial and temporal interpolation methods that exploit PSs obtained by different sensors (and orbits) can be applied. However, these operations introduce uncertainties according to the assumptions made, that not always are satisfied. Integrating InSAR datasets with in-situ static measurements, such as those from a GNSS system, has proven beneficial [139,140].

Additionally, technical constraints make interpretation of the obtained datasets challenging. InSAR data have limited ability to detect north-south displacements. These limitations stem from the polar orbit of SAR satellites and could be mitigated with the launch of satellite missions on specific orbits [74] and the application of 3D deformation reconstruction strategies [60,67,123]. Additionally, InSAR method cannot track rapid (and substantial) infrastructure deformations due to the intrinsic ambiguity of phase measurements [22,141]. Moreover, the revisitation time of SAR satellites, is relatively long [59,60] leading to a low temporal resolution of data. For instance, considering the different wavelengths and revisiting times of satellites like EnviSat, TerraSAR-X, Sentinel-1, and ALOS, the maximum theoretical measurable differential deformation rates are 14.7, 25.7, 42.6, and 46.8 cm/year, respectively. These constraints restrict the applications in which the satellite-based SHM approach can be used.

Given the mentioned limitations and uncertainties, defining damage-sensitive features based on InSAR data can be challenging, particularly when the goal is to differentiate between possible types of anomalies.

4. Population-based structural health monitoring

PBSHM was developed to facilitate monitoring the behavior of populations of similar structures [14,16–18]. This approach arose from the difficulties occurring in producing accurate data-driven models for damage identification in real-world scenarios. These models require extensive training data for each structure, including anomalous instances, which are often inaccessible due to economic and technical constraints. Furthermore, the training data should account for all the variations in the structural behavior induced by operational and environmental factors, a task that is becoming progressively more challenging because of the effects of climate change. PBSHM addresses data scarcity or incompleteness by exploiting knowledge exchange among structures within the same population. Specifically, it leverages information from structures with large available datasets, including anomalous behaviors, to deduce anomalies for those with limited datasets where anomalies have never been identified before via transfer learning algorithms. Consequently, this approach proves highly beneficial for monitoring numerous bridges in extensive infrastructure networks, enhancing SHM even with limited data availability.

To date, the PBSHM strategy encompasses data-driven techniques for conducting SHM, primarily relying on results obtained from dynamic testing, and integrates them with knowledge transfer methods within population data. A brief state of the art on the algorithms employed in PBSHM is reported in the following.

4.1 PBSHM data and algorithms

SHM has rapidly evolved in recent years, mainly due to the adoption of algorithms from machine learning and pattern recognition domains [5,142]. These algorithms handle tasks such as learning classification models, regression models, or probability density functions (PDFs) [143]. A classification task involves assigning a label to any measured sample

to determine if it belongs to a specific damaged or undamaged condition class. On the other hand, a regression model can gauge damage intensity, while learning a PDF can describe the predicted behavior of dynamic features. Constructing these models requires access to extensive and diverse datasets of measurements obtained under various operational and environmental conditions. Furthermore, many SHM approaches rely on supervised algorithms, also needing the associated labels of data instances. However, obtaining such data is seldom feasible, particularly for civil applications.

In PBSHM, a preliminary differentiation must be made between homogeneous and heterogeneous populations. Homogeneous populations [16] consist solely of nominally identical structures that differ only in minor construction details. On the other hand, heterogeneous populations [14,17] may encompass structures that could differ in topology, geometrical properties, materials, and dimensions. Despite these distinctions, the PBSHM approach strives to facilitate knowledge sharing in both scenarios, albeit with variations in the required steps and methods based on the population type.

Homogeneous PBSHM is based on the idea that structurally analogous individuals exhibit similar behaviors, allowing for the construction of a shared model to depict their dynamic characteristics and potential variations. This concept is encapsulated in the notion of "population form", which Bull et al. [16] elaborated on, presenting various construction strategies such as Gaussian processes (GPs) and a combination of GP regression models. Dardeno et al. [144] proposed two approaches to characterize the collective behavior of a homogeneous population of full-scale composite helicopter blades by analyzing their frequency response functions (FRFs) obtained under ambient conditions. Initially, a supervised mixture of GPs was employed to learn the population form. Subsequently, an overlapping mixture of GPs was employed, and the derived population form was used to establish a novelty detection process. Hierarchical Bayesian modeling (HBM) [145] was also applied to the same dataset, expanding the experimental analysis to various environmental conditions. This method concurrently learned the representation of both the population and individual structures, enabling the reconstruction of FRFs in scenarios with limited experimental data and the assessment of temperature variations impacts. HBM has also found application in a multi-task learning framework to represent hazard models for in-service truck fleets and wind turbines [146]. It was also used for enhancing damage detection in a numerical case study involving different offshore wind turbines, based on their natural frequencies [147].

Addressing heterogeneous structures within a population necessitates specific approaches, often relying on transfer learning algorithms. However, these structures may exhibit significant variability in their properties and dynamic features, potentially diminishing the efficacy of knowledge-sharing algorithms. This phenomenon, known as negative transfer [14], occurs when transfer learning algorithms yield inferior performance compared to conventional methods. Hence, research in this domain also focuses on determining the optimal conditions for knowledge transfer, i.e., identifying which structures within the population (potentially, an infrastructural network) can reliably benefit from knowledge transfer through a similarity assessment alongside decision-making theory. The adopted workflow is outlined in Fig. 3. To enhance decision-making, robust risk-based active-learning algorithms have been explored [148], examining the expected value of perfect information (EVPI). Additionally, Hughes et al. [149,150] proposed a framework for informing decisions regarding transfer learning techniques based on the expected value of information transfer (EVIT).

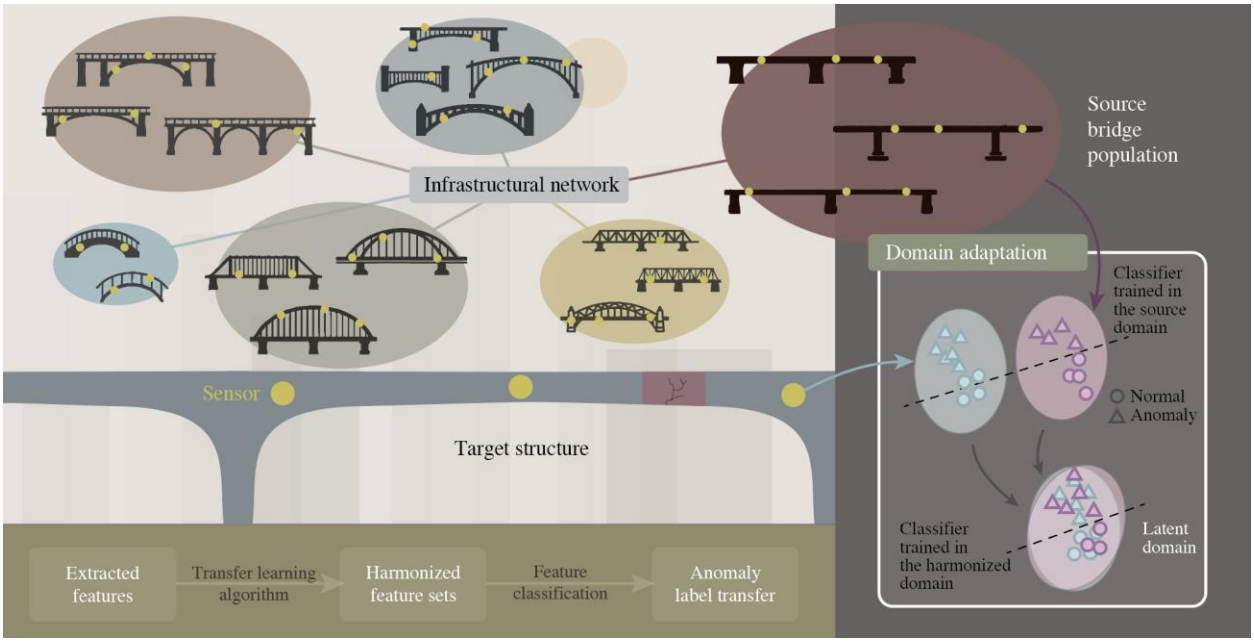

Fig. 3 – Scheme of the population-based monitoring approach and the domain adaptation rationale

The necessity of defining the criteria for sufficiently similar structures to facilitate knowledge transfer led to the development of similarity assessment tools and frameworks for their utilization [14]. Similarity assessment entails automated comparisons between structures. To automatize this process, abstract structural models need to be formalized in an objective manner. Irreducible element (IE) models and attributed graphs (AGs) have been proposed to this aim, drawing inspiration from graph theory [14,15,151]. Specifically, an IE model divides the structure into subcomponents and small elements representative of its behavior at a specified level of detail (granularity). Relationships between elements are established, and properties are stored for each element and relationship. This information is then translated into the AG structure, with nodes and edges representing the structural topology, and attributes storing various properties (e.g., element type, contextual labels, materials, geometry, dimensions). The first similarity metric proposed in the literature involves evaluating the maximum common subgraph (MCS) between structures to determine identical subcomponents, supplemented by the Jaccard Index for similarity measurement [13–15]. However, to account for attribute effects, additional similarity metrics have been proposed, including graph-kernel methods [152] or graph matching networks (GMNs) [153–155]. Furthermore, Poole et al. [156] suggested the modal assurance criterion (MAC) as a measure of data similarity to identify features that minimize shifts between class-conditional distributions and enhance feature extraction, testing this approach thought an experimental case study involving two helicopter blades. Nonetheless, only preliminary studies have been conducted on tools so far, and establishing a broadly applicable threshold for determining when to apply transfer learning remains an ongoing research challenge.

Once the similarity between structures has been defined, the next step in performing PBSHM involves applying transfer learning algorithms to enhance damage identification. The choice of algorithm depends on several factors, including the monitoring task (such as damage detection, localization, damage type definition, extent, and prognosis), the available damage-sensitive features, the level of heterogeneity of the population, and the extent of data scarcity for the target structure [157]. Many studies have focused on domain adaptation (DA) algorithms, which address scenarios where source and target features exhibit different marginal and class-conditional distributions, aiming to learn a feature transformation that minimizes their disparity [158]. A scheme on how domain adaptation operates on source and target features is shown in the bottom-right part of Fig. 3. Gardner et al. [159] introduced DA concepts for SHM, implementing three techniques: transfer component analysis (TCA), joint domain adaptation (JDA), and adaptation regularization-based transfer learning (ARTL). Specifically, TCA computes a feature transformation to

minimize differences between marginal probability density functions (i.e., feature distributions without label information). JDA aims to minimize differences between class-conditional probability density functions for each potential damage class, requiring iterative pseudo-label estimation due to the absence of true labels. ARTL enhances classification using a hyperplane-based classifier and regularization theory. Additionally, another transfer learning approach consists of the kernelized Bayesian transfer learning method [160], implemented to infer a discriminative classifier from inconsistent and heterogeneous feature data. These techniques have been tested across various case studies, including numerical homogeneous populations of multi-story structures and heterogeneous populations comprising both numerical and experimental multi-story structures.

Among the surveyed studies, some of the proposed DA methods are implemented directly using the acquired transfer functions as damage-sensitive features. Specifically, Bull et al. [161] employed TCA to transfer knowledge between similar aircraft wings for damage detection, employing FRFs as damage-sensitive features. Subsequently, Gardner et al. [162] adopted transmissibility paths and implemented the balanced distribution adaptation (BDA) to transfer damage-localization knowledge between different experimental datasets, training the k-nearest neighbors (kNN) classifier on the latent space of labeled source data for classification. Conversely, some studies have examined the use of natural frequencies as input features, as in the case of Poole et al. [163], where statistical alignment (SA) has been proposed as a low-risk form of DA.

4.2 PBSHM bridge benchmarks

While existing literature on PBSHM primarily focuses on its theoretical formalization [14,16–18], some practical applications have been conducted, primarily within the aerospace field [153,161,162] and wind turbines [147,159], with a growing number in the domain of bridges [13,164–166]. Typically, the case studies regarding mechanical and aerospace components involve laboratory tests, whereas real-world applications predominantly pertain to civil structures. Within the civil engineering domain, these studies can be further categorized based on their research focus. Most articles introduce and implement methodologies to enhance damage identification, achieving varying levels of identification accuracy. Simultaneously, another branch of research involves preliminary investigations into representing structure populations, methods for assessing structural similarity, and strategies for evaluating the significance of these analyses while quantifying the risk associated with knowledge transfer. The rest of this section focuses on applications involving bridge benchmarks.

A promising class of algorithms in civil applications is the SA, which can be adopted independently for simple knowledge-sharing problems or as a preprocessing step for addressing more complex tasks [162]. SA involves learning a feature transformation solely from normal (undamaged) condition samples across domains, aligning their lower-order statistics. Poole et al. [163] demonstrated how SA can enhance damage identification, for instance, through the application of a KNN classifier. This method has been applied to a numerical case study simulating shear structures and a diverse real-world population, which includes data from the Z24 post-tensioned concrete two-cell box-girder road bridge [167] and the KW51 steel single-span tied arch railway bridge [168], for which datasets collected in separate experimental campaigns are available under request. Giglioni et al. [166] employed the same method for knowledge sharing between the Z24 bridge and the S101 post-tensioned concrete road bridge [169], another example of bridge on which controlled tests were performed and the data were made available for researchers. By leveraging the similarity between these bridges, both featuring three spans and a continuous deck over the piers, SA improved damage detection performance.

Yano et al. [170] applied different transfer learning strategies for analyzing a separate population of real bridges, namely the Z-24 bridge, the PI-57 post-tensioned segmental bridge [171], and the PK 075+317 reinforced concrete railway bridge [172]. They used natural frequencies as damage-sensitive features and conducted knowledge sharing through TCA, JDA, and maximum independence domain adaptation (MIDA). Luleci et al. [164] introduced another methodology for feature harmonization, employing structural state translation (SST) to transfer information between prestressed bridges. They used the domain-generalized cycle-generative (DGCG) model, trained on data from one source bridge and generalized to data from a second target bridge. This approach translates the source state to the target state, which is then compared to the actual state to evaluate performance.

Figueiredo et al. [173] proposed the use of transfer learning strategies between real bridge data and simplified numerical models of the same structures. They exploited domain adaptation algorithms, particularly TCA, to harmonize a classifier based on the FEM of the structure, serving as the source domain, and then transferring it to the real structure, serving as the target domain. This approach is particularly effective for structures with no available historical data.

Another research trend in this field concerns the use of deep convolutional neural networks (CNNs) and fine tuning [174–176]. Pan et al. [174] implemented a novelty detection approach, training the network on data from a source bridge in different conditions. Subsequently, the knowledge is transferred to a target bridge using fewer target data to fine-tune the network. In particular, the parameters of the pre-trained CNN with the best performance are transferred to the target bridge.

Additionally, some studies have explored alternative transfer learning approaches for SHM that, while not strictly conforming to the PBSHM framework, share a similar underlying philosophy. For instance Tronci et al. [165] proposed a novel monitoring strategy for bridges that does not rely on transferring knowledge from a specific bridge case study but instead uses speaker registrations as a source for transfer learning. This method is based on the rationale vocal chords are vibrating structures, and features that characterize different speakers may help in identifying damage conditions. Leveraging a comprehensive audio dataset of vibration records, a linear discriminant analysis classification model is trained. Subsequently, this knowledge is transferred to classify Z24 bridge monitoring data, with Mel-frequency cepstral coefficients serving as the features facilitating the transfer process.

Ierimonti et al. [177] investigated a method to generate multiclass labels based on a surrogate model of a structure, constructed using its FE model, to generate sensitivity damage charts, which function as class classifiers. Finally, Bayesian model updating of the damage-dependent parameters enables probabilistic damage identification, facilitating knowledge transfer between a numerical model and real monitoring data obtained from the Consoli Palace, a monumental building situated in Gubbio, Italy.

4.3 Current challenges in PBSHM

The aforementioned studies highlight the potential advantages of leveraging shared knowledge between similar source and target structures. Techniques like DA offer solutions to the challenges posed by using different datasets in the training and testing phases of data-driven monitoring algorithms [159]. However, there are still difficulties regarding the broad applicability of these strategies across entire networks or populations of structures.

First, there is a need to further explore the link between similarity assessment and the actual transfer learning phases, along with defining a threshold for applying these strategies [151]. Once structural information is encoded into AGs, criteria must be established to determine which information level should be considered when identifying common subgraphs. For instance, in dynamic SHM problems, factors that impact masses and stiffness need to be accounted for; however, this may not always be the case for other types of features.

Furthermore, while PBSHM facilitates the comparison of structural features, the traditional SHM approach based on historic baseline data is still prevalent, relying on past data that may not be available for all structures within the population. Additionally, while PBSHM offers insights into structures with limited data on damaged conditions, it still requires training data (i.e., the alignment process in the DA realm). However, due to limitations of on-site sensors, limited data may be available for all structures of interest. Indeed, deploying sensors across a wide population may incur significant costs for administration.

5. Roadmap for regional-scale structural health monitoring

PBSHM enables sharing knowledge among structures, leveraging past occurrences in similar individuals to improve anomaly characterization. Integrating PBSHM with ISHM and InSAR data can be advantageous due to the ease of obtaining the data required for constructing transformation maps required for DA techniques and obtaining damage labels. However, this integration necessitates the definition of new features compared to those commonly used in current literature on PBSHM, which typically consist of natural frequencies acquired through OMA. These new

features must be (1) sensitive to the targeted anomalies and (2) consistent in dimensionality across different structures. Although features with different dimensions may also undergo specific dimensionality transformations to address label space inconsistencies [17], this roadmap only considers standard DA approaches.

While OMA boasts a relatively extensive history, underscoring the consistency and sensitivity of natural frequencies to damage states linked with structural stiffness variations, static data retrieved from InSAR and high-noise measures obtained through ISHM necessitate new approaches. Nevertheless, the previous sections showed that these two measurement types, one static and the other dynamic, complement each other in the sensitivity to different types of structural damage. Specifically, static measurements are particularly sensitive to displacements and deformations, which can be due to settlements and scour, while dynamic measurements are sensitive to variations in structural stiffness, mainly caused by variations in the cross-sections of the structural elements or connection issues. Based on the phenomena of interest, a different set of features can be formed, based on one of these approaches, or both.

Fig. 4 illustrates a possible framework for regional-scale SHM based on the surveyed approaches. Data are collected through drive-by and/or remote sensing for structures in the monitored region and for similar structures worldwide to form bridge populations. The structures in the latter set (Fig. 4, sector "Damage database") constitute the source domain, while the monitored structures (Fig. 4, sector "Near-real-time monitoring") form the target domain. Structures in the source domain should be selected from those that have experienced anomalies in the past. Properly defining the features from the collected data will allow the use of anomaly labels from the source structures to classify potential issues in the target structures. Based on the potential and challenges that emerged in the previous sections, a roadmap is proposed herein to foster this framework. Issues, needs, and potentiality of this new approach are outlined and discussed.

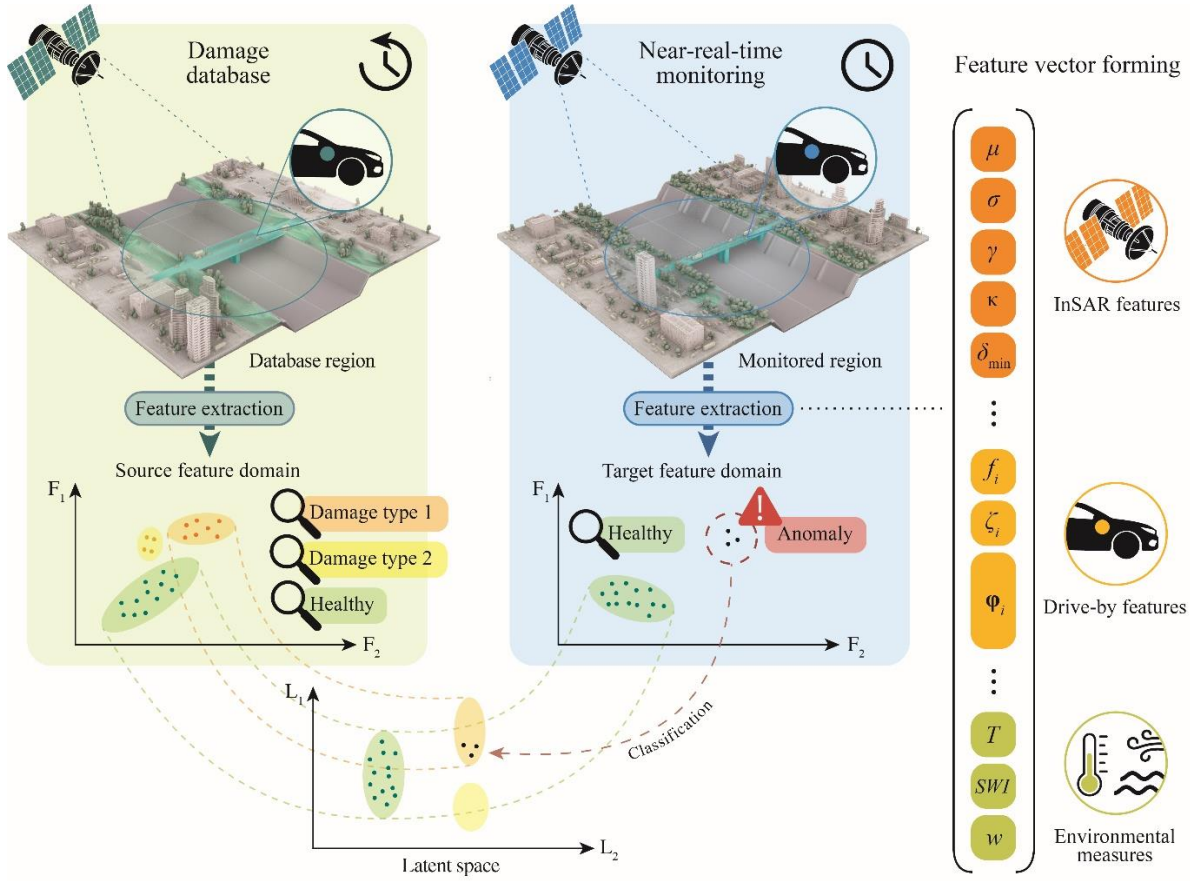

Fig. 4 – Framework for regional-scale structural health monitoring

5.1 Similarity assessment

The first aspect to address regards the similarity assessment. The complementary nature of the phenomena observed through drive-by and satellite data highlights the challenge of establishing criteria for similarity assessment within a population of structures. Ensuring positive transfer, whereby knowledge from one structure informs others, hinges on robust similarity assessment aligned with the features (and consequently the data) used in PBSHM applications. This section discusses the meaning of similarity assessment and highlights possible aspects to be considered with the newly proposed approach.

First, it is essential to conduct similarity assessments with consideration of the specific phenomena of interest during the monitoring phase. Adopting overly strict approaches, under the assumption that they ensure positive transfer, will inevitably restrict the available populations, thereby compromising the applicability of the approach.

For instance, consider a population of bridges with simply supported decks. If the PBSHM features are natural frequencies (derived from structural vibration responses), the types of anomalies that can be identified are those producing variations of the mass and/or stiffness. Thus, similarity assessment must encompass relevant parameters that impact these quantities, such as material properties, section geometries, and connections between elements. Indeed, sharing information about corrosion in one element of a simply supported steel truss bridge may not be informative for damage characterization of a simply supported reinforced concrete bridge, as the damage label cannot be easily interpreted in the context of the second structure. Conversely, when analyzing static displacements (e.g., from InSAR data), observed bridge behavior primarily reflects variations in boundary conditions (e.g., support settlements). Here, the nature of the bridge span (material, mass, cross-section) plays a less significant role. For example, two simply supported bridges are likely to behave similarly if their piers exhibit similar sensitivity to environmental drivers, regardless of the material and cross-section shape of the deck.

Considering the outlined factors, applying PBSHM to drive-by features necessitates a similarity assessment analogous to those employed in studies using vibration data. However, it remains unclear whether vehicle type and pavement conditions should be included into this assessment, as they may influence the identified features, as discussed in Section 2.1. On the other hand, applying PBSHM to InSAR data demands similarity assessment based on high-level bridge features (e.g., span length, support conditions), and requires evaluating the similarity of soils and environmental factors (e.g., temperature, river crossings), typically achievable if a regional-scale approach is applied to a relatively confined geographic area or if all bridges are aligned along the same route (e.g., highway or river) [135]. Furthermore, in this context, the orientation of the bridge plays a crucial role (as discussed in Section 3), and its inclusion in the assessment process needs consideration.

If a comprehensive procedure encompassing both data types is devised, the parameters included in the similarity assessment phase comprise the union of the two sets of information. However, this condition is not necessarily rare, as bridges and viaducts in confined regions are generally built based on similar design schemes. Fig. 5 illustrates two examples of bridge populations on the A13 highway. The first (a) consists of single-span prestressed reinforced concrete bridges with 4-8 I-shaped beams (over 30 instances can be counted spanning from km1 to km38). The second (b) consists of steel-concrete composite bridges with 2 I-shaped steel beams (there are over 30 instances between km38 and km80). Bridges within the same population share clear similarities in materials, size, and structural configurations.

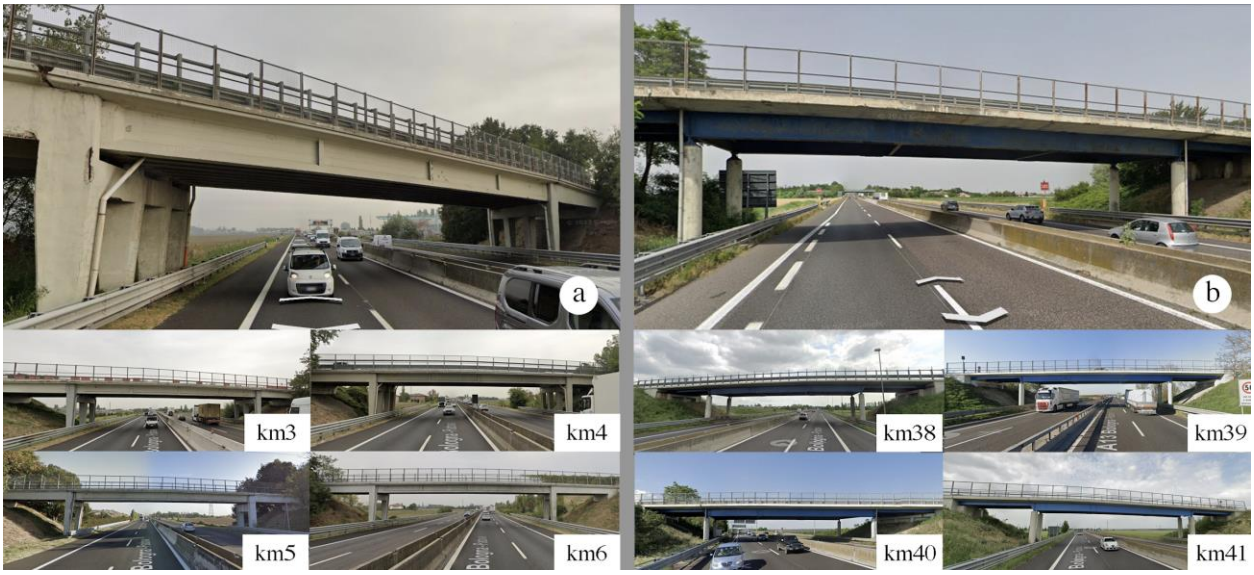

Fig. 5 – Two examples of bridge populations: (a) prestressed reinforced concrete bridges, (b) steel-concrete composite bridges

5.2 Data availability

The second aspect is related to data availability. Two datasets are required to implement a regional-scale SHM process using drive-by and satellite measurements. The first dataset comprises data from the population of interest that requires monitoring, for which information on current and past structural issues may be unavailable. The second dataset consists of information from similar bridges, which can also be in different geographical regions, that have exhibited certified anomalies in the past. Possessing both datasets enables the application of knowledge transfer strategies to obtain insights into potential anomalies affecting the monitored structures.

Regarding remote sensing data, all necessary components to accomplish these objectives are readily accessible. Displacement data can be sourced from various agencies. For instance, the European Space Agency offers data collected by TerraSAR-X satellites upon request, while the Italian Space Agency provides data gathered by COSMO-SkyMed. Additionally, the EGMS [178] has been developed within the European project Copernicus, enabling the free download of data captured by Sentinel-1 satellites.

Displacement data can also be collected from these systems for bridges with certified anomalies. The datasets acquired for specific bridge sites can be structured into databases that outline bridge characteristics, anomaly types, and the time frames when anomalies occurred. This organization allows for the retrieval of data compatible with the monitored population of structures, which can then be employed to train an anomaly classifier. Extensive literature exists on historic bridge collapses, with numerous studies investigating their causes in various countries, including China [179,180], Colombia [181], the United States [182–184], India [185], and more [186–188]. Additionally, research focusing on specific bridge types or collapse causes, such as metallic bridges [189,190] or hydraulic collapses [191], provides several examples. These studies can be used to determine the locations and time intervals in which satellite data can be retrieved for a specific anomaly of interest.

Moreover, papers that investigated bridge behavior/anomalies based on satellite data should be used to define the types of anomalies observable for specific bridge types. Table 1 reports some examples of these studies together with the bridge type and observed phenomena.

Table 1 - Summary of relevant case studies for InSAR-based SHM

Reference	Bridge	Bridge type	Data source	Period	Observed phenomenon
[90]	Aylesford Bridge, UK	Arch masonry bridge	SNT	2015-2017	Water level dependency and riverbed soil expansion
[192]	Blackfriars bridge, UK	Arch masonry bridge	SNT	2015-2021	Thermal expansion
[12,129]	Tadcaster Bridge, UK	Arch masonry bridge	TSX	2014-2015	Scour and deck deformation
[193]	Amsterdam bridge network, the Netherlands	Different types	TSX	2009-2016	Land subsidence
[194]	Ponte dell'Industria, Celico bridge, Bisantis bridge, Italia viaduct, Morandi bridge, Italy	Different types of RC bridges	CSK	2016-2018	Deck deformation
[118,120]	Seitenhafenbrücke bridge, Austria	Integral RC bridge	SNT	2011-2017	Thermal expansion and water level dependency
[195]	A22 Po River Bridge, Italy	Multispan RC bridge	CSK	2014-2022	Thermal expansion and water level dependency
[75,128]	Albiano-Magra Bridge, Italy	Multispan RC bridge	CSK	2015-2020	Settlement and deck deformation
[196]	Beishatan bridge, China	Multispan RC bridge	CSK	2011-2017	Differential subsidence
[197]	N3 bridge, the Netherlands	Multispan RC bridge	ERS, ENV, RADARSAT, TSX	1995-2018	Settlement
[198]	Santa Clara River bridge, Pleasant Valley bridge, and Third Street Overcrossing bridge, California, USA	Multispan RC bridge	ENV	2005-2010	Land subsidence
[85]	Valencia harbor Bridge, Spain	Multispan RC bridge	ALOS, CSK	2007-2012	Settlement and angular distortion
[199]	Radotín bridge and Svinov bridge, Czech Republic	Multispan RC bridges	TSX	2013-2015	Thermal expansion
[78]	Eltham bridge and Lord Dealwere bridge, Virginia, USA	Post-tensioned RC bridges	TSX	2016-2018	Thermal expansion
[83]	Morandi Bridge, Italy	Prestressed RC cable-stayed bridge	ENV, CSK, SNT	2003-2018	Deck deformation
[119]	Waterloo Bridge, UK	RC arch bridge	TSX	2017-2018	Thermal expansion
[200]	Rainbow bridge and Lupu bridge, China	RC arch bridge, Steel arch bridge	CSK, SNT, TSX	2013-2018	Differential subsidence
[70]	Himera viaduct, Italy	RC bridge	CSK	2011-2014	Settlement and angular distortion
[201]	Jing-Shi HSR bridge, China	Simply-supported RC bridge	CSK	2014-2017	Settlement and uplift
[202]	Dashengguan bridge, China	Steel arch bridge	SNT	2015-2016	Thermal expansion
[203]	Lupu Bridge, China	Steel arch bridge	CSK	2008-2010	Thermal expansion
[204]	Nanjing-Dashengguan Railway Bridge and Nanjing-Yangtze River Bridge, China	Steel arch bridge, Steel truss bridge	SNT	2015-2018	Thermal expansion
[205]	Hintze Ribeiro bridge, Portugal	Steel bridge	ERS	1995-2001	Scour
[123]	Palatino bridge, Italy	Steel bridge	CSK	2011-2019	Thermal expansion

[206]	Cornwall Highway bridge, Canada	Steel truss bridge	RADARSAT	2014-2016	Thermal expansion
[207]	Moerdijk bridge, the Netherlands	Steel truss bridge	TSX	2009-2015	Settlement
[208,209]	Ponte Della Musica–Armando Trovajoli, Italy	Pedestrian steel arch bridge	CSK	2011-2019	Thermal expansion and land subsidence

To date, unlike satellite data, drive-by recordings are rarely accessible. While some studies have been conducted to specifically capture data from selected structures, only a few are openly available [39,210]. However, in the near future, more testing campaigns will be planned [211]. Nonetheless, the current state of development of the methodology and experimental campaigns still falls short of providing comprehensive data for regional-scale SHM. The primary reason is the lack of crowd-involved projects. Challenges related to involving citizens in retrieving the data include potential privacy policy issues, the non-standard usage of sensors in smartphones (the primary data source) while in transit, and the diverse technical specifications among different sensing devices that people may possess. To mitigate these issues, initial campaigns in the future should involve collecting data from shared vehicles equipped with standard sensors and vehicle structures [38].

5.3 Feature extraction

Feature extraction is a key process to implement regional-scale SHM. Recent studies reviewed in Section 2 have introduced tailored methods for extracting natural frequencies from drive-by measurements. Therefore, this feature remains applicable if PBSHM is based on drive-by data, along with modal damping, although few studies have explored its sensitivity to damage and estimation accuracy, especially under drive-by conditions. Furthermore, for ISHM methods capable of identifying mode shapes, average parameters estimated over the bridge length should be used, which are not strictly dependent on the bridge size. For instance, the average modal curvature, obtained upon defining a standard normalization for identified modes, is as an indicator of global stiffness reductions.

Regarding displacement measurements, they must be sensitive to conditions that may lead to failure mechanisms, involving excessive displacements of structural elements. A preliminary study on implementing PBSHM with displacement data demonstrated that statistical moments (mean, standard deviation, skewness, kurtosis), along with other statistical indicators (maximum/minimum displacement) calculated from displacements measured at different PSs at a given instant, are representative features [135]. Various features related to different structural components (e.g., piers, abutments, deck) should be used based on the specific damage of interest. However, additional details derived from analyzing PSs obtained on different sections of the bridge necessitate high-resolution data. Therefore, feature definition is also strongly influenced by the type of data, as discussed in Section 3.1. In this context, preliminary analyses to assess the sensitivity of different feature sets to various types of anomalies, using synthetic data obtained from simplified models, are strongly recommended.

The right part of Figure 4 - "Feature vector formation" - illustrates an example of constructing a feature vector from available InSAR and drive-by data, highlighting the core integration between these two monitoring methods. The first part of the vector consists of features that can be consistently derived from InSAR data across the structure population. Examples of features that capture the global structural behavior are statistical moments, such as mean (μ), standard deviation (σ), skewness (γ), kurtosis (χ), as well as minimum/maximum ($\delta_{\min}/\delta_{\max}$) of displacement measurements at various control points (which may correspond to PSs or be derived from multiple PS measurements at strategic locations). The second part of the feature vector can include parameters obtained from drive-by measurements, such as modal frequencies, damping ratios, and compact features derived from identified mode shapes, ensuring consistency across structures. In addition to structural features, environmental measures are crucial for anomaly detection. Satellite measurements can provide estimates of air temperature (T) or ground properties (such as the soil water index – SWI [212]), directly contributing additional features to define both source and target domains [135,195]. Examples of environmental data obtained from satellite measurements include the ERA5 model [213] or its land-

specific reanalysis ERA5-Land [214]. Additionally, locally collected data from weather stations or river monitoring stations (such as the water level of a river at the bridge site – w) could be incorporated, if available. Given the differing temporal availability of the mentioned features, developing an appropriate method for determining when to generate new feature instances requires further detailed study.

5.4 Implementation of the regional-scale approach

After defining a set of new features for each data type (i.e., drive-by, satellite, and environmental), these features should be appended to define the overall dimensionality of the source and target domains. Three scenarios emerge: applying the strategy solely to drive-by data, to InSAR data, or adopting a comprehensive approach. Additionally, environmental data can be included or excluded in all scenarios. The first two scenarios are the simplest, both in terms of similarity assessment and of feature definition. In the third case, or when environmental data are included, particular attention must be paid to the differing temporal resolution of the different types of datasets. In such cases, time interpolation strategies may be necessary.

In a regional-scale monitoring approach, if environmental drivers causing feature fluctuations (e.g., temperature) are comparable across structures, comparisons between structures can be made without the need for a "baseline" or "reference" dataset collected in the past under assumed anomaly-free conditions. Once structural features are harmonized, they should undergo the same variations due to common environmental drivers. Therefore, if one bridge in the population deviates from the others, it is likely to be anomalous. This approach, applicable only if structures are observed within a confined region, can be particularly useful due to increasingly extreme environmental conditions driving bridge behaviors, linked to climate change. For instance, if an abnormally high-temperature value causes significant shifts in the natural frequencies and static displacements of bridges due to thermal variations, comparing these features with historical data would produce outliers, typically interpreted as damage states. However, if all bridges are affected by the anomalous temperature value in the same way, it would not be detected as an anomaly. Moreover, this process would also reduce reliance on historical data, which may not be easily obtained, especially for ISHM.

6. Conclusions

Recent studies aimed at assessing the health state of transportation infrastructures have raised the need for extensive knowledge on multiple structures within vast territorial regions. In this direction, traditional SHM based on on-site data may fall short due to the cost of monitoring systems and data management.

The integration of satellite sensing and ISHM techniques with PBSHM shows great potential for improving structural and damage identification. While both static and dynamic measurements offer complementary insights into bridge conditions, defining new features and addressing challenges such as dataset resolution and accuracy remain critical, thus needing experimental validation.

This paper lays the groundwork for a new research direction in regional-scale SHM using both drive-by and satellite remote monitoring data. Decades of collected satellite data worldwide and published surveys on known bridge anomalies can be leveraged to build databases for a satellite-based approach. This paper presented an example of database that could be used to form bridge populations and share information based on InSAR data. However, validating the proposed framework with drive-by data remains unfeasible due to the lack of available data. Collaborative efforts between researchers, practitioners, and policymakers are crucial for advancing data-collection initiatives involving the population.

Future directions for defining static and dynamic feature sets and similarity assessment rules have been outlined, emphasizing their dependence on the types of damage being studied and the nature of the processed data. Additionally, exploring history-free procedures, which do not require extensive baseline datasets but instead rely on differences among similar bridges under common environmental conditions, has emerged as a potential avenue for further development.

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