



A Comparative Study of Global and Local Damage Detection Techniques Used in Structural Health Monitoring of Civil Structures

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Abstract. Structural health monitoring systems, which operate as SHM systems, need to function to maintain sustainable and secure operations for civil infrastructure. The SHM damage detection systems use two different methods to identify structural damage. The first approach assesses the overall state of a structure using global approaches. The second approach looks for damage within specific materials or components using local techniques. The research examines both regional and international methods that are used to detect structural damage in civil construction projects. The research investigates eight common SHM methods, which include vibration-based, strain-based, displacement-based, acoustic emission, guided-wave and ultrasonic, smart-material-based, modal identification, and data-driven approaches. The paper provides a detailed explanation of their sensing processes, together with their damage indicators, advantage and disadvantage assessment, and practical application demonstration. The review follows a comparative study to provide reproducibility and transparent research results. The study concludes with significant research gaps and future goals, particularly regarding the emerging topic of hybrid SHM frameworks and reinforced concrete buildings. The approaches are contrasted to demonstrate their compatibility with various types of damage.

Keywords: Structural Health Monitoring, Global Damage Detection, Local Damage Detection.

1 Introduction

Buildings, bridges, and dams are civil infrastructure. They are increasingly influenced by ageing, environments, and extreme loading events. To inspect them, people usually use existing approaches. These approaches usually depend on periodical visual inspection. The results may be subjective and unable to find hidden or incipient damage. Thus, Structural health monitoring (SHM) becomes a data-driven approach. SHM uses in-situ sensors to measure and monitor the civil infrastructure in a continuous or periodic way [1–3].

Structural Health Monitoring (SHM) is commonly treated as a statistical pattern recognition problem, where changes in the measured structural responses are utilised to detect the presence of damage [1]. Damage modifies physical response characteristics such as stiffness, mass, and damping that are consequently reflected in vibration, strain, displacement, and stress-wave responses [4]. A common hierarchy of SHM capabilities consists of damage identification, localisation, severity estimation, and remaining life estimation [5–7].

From a spatial point of view, structural health monitoring (SHM) techniques can be mainly categorised into global and local damage detection methods [8]. Global methods capture changes in the structure's global behaviour, while local methods focus on detecting damage at its origin. Recognising this fact helps in the proper choice of SHM strategies and also motivates research on hybrid monitoring approaches.

2 Global and Local Damage Detection Concepts

2.1 Global Damage Detection

Structural health monitoring (SHM) methods capable of monitoring global changes in the system-level properties are sensitive to changes occurring in the system's natural frequencies, mode shapes, and damping ratios. Vibration-based SHM is the most popular type of global SHM technique because it can be applied efficiently to structures of large scale with a relatively sparse sensor network [9]. Global methods are less sensitive to small or localised damage. This is especially true for statically indeterminate structures [10].

2.2 Local Damage Detection

Local Structural Health Monitoring (SHM) methods are designed to detect damage at or near its origin, making them particularly sensitive to early-stage defects. Techniques such as strain-based monitoring, acoustic emission (AE), and ultrasonic guided waves are included in this category. While these local methods are highly sensitive, they often require a dense deployment of sensors and typically provide limited information about the overall performance of the structure [11].

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2.3 Hybrid Global–Local SHM

To facilitate comprehensive multilevel damage evaluation, recent studies emphasize the significance of hybrid Structural Health Monitoring (SHM) framework that combine global and local techniques [12,13]. In these systems, local methods focus on the onset and development of deterioration, whereas global methods focus on the deterioration of the structures. Machine learning methods and data fusion have greatly improved the efficiency of hybrid structural health monitoring systems [14].

3 Research Methodology

The methodology adopted for conducting this study is based on an extensive comparative analysis of eight key Structural Health Monitoring (SHM) techniques. The researchers have used key data sources like Scopus, Web of Science, ScienceDirect, Google Scholar, etc., to collect the research articles. To evaluate all eight SHM techniques, the researchers have performed tests to assess their ability to detect damage, their ability to detect damage in specific areas, data requirements, accuracy, and their efficiency while operating civil infrastructure systems.

4 Global SHM Techniques

4.1 Vibration-Based Methods

Vibration assessments, which are based on changes in dynamic characteristics (natural frequencies, mode shapes, and equivalent damping ratios) where these parameters depend on changes in stiffness, mass, or energy dispersion due to damage, are one of the oldest and most prominent methods used to check the condition of civil structures [15,16]. Signals from a variety of sensors, including accelerometers, are used to monitor controlled inputs or ambient excitations (wind, traffic, microtremors). Time-domain and frequency-domain techniques like the Fast Fourier Transform (FFT), Frequency Domain Decomposition (FDD) [16], and Stochastic Subspace Identification (SSI) are used to determine modal parameters [16,17]. The technique is suited for ongoing monitoring, non-destructive, and economical for large buildings. But generally speaking, vibration-based Structural Health Monitoring (SHM) is more sensitive to global damage. The technique is suited for ongoing monitoring, non-destructive, and economical for large buildings. However, climatic and operational factors like temperature and loading conditions might affect vibration-based structural health monitoring (SHM), which is generally more sensitive to global damage than localised damage [10]. Current research aims to enhance damage sensitivity by employing advanced signal processing techniques and data-driven methods.

4.2 Displacement-Based Methods

This SHM method emphasises the measurement of relative structural displacements, such as mid-span deflection, inter-story drift and settlement, to detect, locate, and measure damage or performance reduction [18,19]. Displacement is a key kinematic response related to strain and stress, making it an intuitive indicator of structural behaviour and serviceability. [19]. Damage mechanisms such as cracking, stiffness loss, loosened connections, or foundation settlement occur as alterations in static offsets, relative displacements, or modal displacement shapes over time [20,21]. Displacements are measured using contact sensors such as LVDTs and vibrating-wire sensors, indirect acceleration-based estimation with advanced drift correction, GNSS/RTK systems for large structures, and non-contact techniques like laser, LiDAR, and vision-based Digital Image Correlation (DIC) [22–24]. Displacement data are commonly utilised to monitor inter-story drift, assess settlement, compare modal shapes, and update finite-element models [19,23,25]. This method offers high sensitivity to local damage and provides a clear physical interpretation. However, it faces challenges related to sensor deployment, environmental effects, and uncertainty in displacement estimation. This situation motivates ongoing research in sensor fusion and robust algorithms [18,21,26].

5 Local SHM Techniques

5.1 Strain-Based Methods

The present method assesses the local deformation of structural elements to determine the stress redistribution patterns that affect stiffness changes and damage progression, together with the operational capabilities of the structure. The relationship between strain and stress through Hooke's law ($\sigma = E\varepsilon$) enables observers to use strain field measurements as accurate indicators of material cracking and yielding, together with changes in load distribution patterns [27,28]. The monitoring system for strain uses electrical resistance strain gauges and vibrating-wire sensors, which operate for extended periods of time, together with Fibre Bragg Grating (FBG) sensors and distributed fibre-optic sensing (DFOS) technology that enables continuous strain measurements across

extensive civil infrastructure systems such as bridges, tunnels, and pipelines [29–32]. The researchers used time-domain trend analysis, fatigue cycle counting, modal strain shape analysis, and inverse finite-element model updating to process strain data and identify and measure damage in the research [27,31,33]. Recent advancements in the field include the development of machine-learning-based anomaly detection systems that leverage large DFOS datasets from dense installations [34]. Strain-based structural health monitoring systems offer excellent sensitivity for monitoring and deliver clear physical results, making them usable in embedded systems to monitor fatigue and crack development [27,29]. The existing problems with temperature compensation and sensor durability, together with data volume handling needs and requirements for accurate damage assessment, drive research into data fusion methods, inversion techniques, and standardisation processes [31,35].

5.2 Acoustic Emission (AE)

The system operates as a passive and non-destructive structural health monitoring system which detects high-frequency stress waves that occur when strain energy suddenly releases from structural elements through active damage processes, which include crack initiation, crack growth and fibre breakage and corrosion [11,36]. The AE system detects real-time damage progression through direct measurement which provides precise time information about damage events while vibration-based methods monitor complete property changes. The system uses piezoelectric sensors and high-rate data acquisition to identify Acoustic Emission events which display features of amplitude and energy and duration and frequency content [11,37]. The system uses sensor arrays to determine damage sources through time-difference-of-arrival and beamforming and time-reversal techniques [38,39]. The concrete bridges and prestressed structures and composite materials and pipelines and pressure vessels of AE have become common testing sites which often reveal micro-damage that precedes visible cracking [40,41]. The system provides high monitoring sensitivity with real-time capabilities but faces various challenges which include noise interference and wave diminishing effects in complex media and needs for active forces and difficulties with damage assessment through quantitative methods [11,36]. The ongoing research work aims to develop reliable methods for processing signals and to create machine-learning systems for classification and to implement systems that can locate problems in intricate facilities and to combine different data types into one system [37,42].

5.3 Ultrasonic and Guided Wave Methods

This SHM technique uses high-frequency elastic waves which range from tens of kHz to MHz to travel through structural elements and detect defects which include cracks and corrosion and delaminations [43,44]. Guided waves (e.g., Lamb waves) show both dispersive properties and multiple modal patterns because damage affects their speed and their loss of energy and their modal characteristics which create distinct reflection and scattering patterns [43]. UGW methods which use piezoelectric wafer active sensors (PWAS) and EMATs and laser ultrasonics enable long-distance inspection with minimal sensor systems and exceptional detection capabilities for tiny or concealed fault. The typical methods for damage detection include baseline comparison time-of-flight analysis correlation-based damage indices and the growing use of machine learning for anomaly detection and imaging purposes [44]. These methods find common use in pipeline systems and aircraft composite materials and bridge structures and wind turbine blades [43]. Current research focuses on solving important problems which include dispersion complexity and environmental variability and attenuation across heterogeneous materials and sensor durability and the measurement of damage size [45].

6 Smart Material-Based SHM

The structural health monitoring (SHM) method uses materials which convert physical or mechanical changes into measurable electrical or optical signals for the purpose of detecting, locating, and assessing structural damage. The main important technologies include fiber-optic sensors (FBG and distributed optical fibres), which deliver high-resolution monitoring of strain and temperature through EMI-immune capabilities that last for extended periods, and piezoelectric sensors (PWAS/PZT), which function as both actuators and sensors for guided-wave and impedance-based damage detection, and self-sensing cementitious composites, whose conductive fillers permit distributed damage detection through resistance changes [46]. The active piezoelectric techniques (pitch-catch and impedance) effectively identify small localised damage, while the passive or quasi-static techniques (FBG and self-sensing concrete) enable continuous monitoring of infrastructure over extended periods. The signal processing method utilises time-frequency analysis and damage indices together with advanced machine learning techniques for both anomaly detection and environmental compensation purposes [47]. The applications include bridges together with buildings, aerospace composites, and pipelines. The research continues because the existing solutions for highly sensitive multifunctional systems encounter issues with product life, environmental impact, and financial constraints, and accurate damage assessment [48].

7 Data-Driven and AI-Based Methods

The SHM methods establish normal structural operations by analyzing sensor data which includes vibration and strain and displacement and image measurements through statistical methods and machine-learning algorithms. The system detects damage when it observes new data that sharply diverges from established baseline patterns which do not depend on developing a complete physics-based or finite-element model [49]. The standard workflow process begins with data collection and data preparation work before moving into the data extraction phase which includes time-based and frequency-based and time-frequency-based and modal-based feature extraction methods and PCA-based dimensionality reduction and overall performance evaluation through supervised and unsupervised and deep-learning ANNs and SVMs and CNNs and autoencoders and AR and ARMA models for classification and anomaly detection and regression tasks [50]. The techniques enable organizations to perform automated monitoring and predictive maintenance at large scale, which makes the techniques attractive for monitoring complex systems and monitoring existing systems that do not have precise modeling capabilities. The system faces multiple challenges because it has restricted ability to interpret results and it shows high sensitivity to environmental changes and it lacks sufficient data while it faces difficulties with generalizing outcomes. The research team works on creating reliable SHM systems through their investigation of hybrid physics-informed machine learning and uncertainty quantification and domain adaptability and multimodal data fusion and standardized benchmarking methods [51].

8 Model-based & Analytical-Based

The SHM techniques use mathematical or numerical structure descriptions, which they develop through finite element method (FEM) modelling, to assess system performance against actual sensor measurements. The system experiences flexibility problems when it shows changes in its modal characteristics, stress patterns, and dynamic behaviour. The model, which has undergone calibration, functions as a digital duplicate of the undamaged structure. The common procedures include constructing a finite element model and using model updating for calibration purposes, establishing a baseline to perform ongoing monitoring, and conducting inverse identification to detect and assess damage through optimisation and Bayesian inference methods [52]. The methods enable maintenance teams to use "what-if" simulations while providing clear physical explanations and delivering damage assessment results, which include measurable uncertainty data for their maintenance planning. The model needs to be accurate, while a dependable baseline must exist, and the system must operate efficiently, because the mathematical problem for inverse solutions becomes difficult to solve when engineers need to find minor damages. The current research investigates hybrid model-data systems, which include uncertainty handling and environmental correction methods, and extensive real-world testing [53].

9 Comparative Assessment

While local approaches are excellent at early damage detection but provide little system-level insight, global methods are useful for general condition assessment but lack localisation capabilities. The most accurate damage assessment is provided by hybrid SHM systems that combine the two methods, especially for reinforced concrete structures.

- Global damage detection is best addressed by vibration-based, model-based, and data-driven SHM, as they capture system-level response changes.
- Local damage detection is more effectively achieved using AE, ultrasonic/guided waves, smart materials, and NDT, which are sensitive to cracks, delamination, or corrosion at specific locations.
- Hybrid SHM frameworks (e.g., vibration-based + guided waves, or model-based + ML) are increasingly adopted to overcome the individual limitations of purely local or global methods.
- No single SHM method is sufficient for all damage scenarios; multi-scale, multi-sensor, and multi-method integration is now recognized as the most reliable strategy for practical structural health monitoring.

Table 1. Comparative analysis of different SHM techniques

SHM Method	Damage Detection Nature	Local / Global Capability	Key Strengths	Main Limitations
Visual Inspection / Conventional NDT	Direct physical observation or point testing	Local	Simple, intuitive, widely accepted; effective when damage location is known	Subjective, labour-intensive, requires access; not suitable for continuous or large-scale monitoring
Vibration-Based SHM	Changes in modal parameters (frequency, mode shapes, damping)	Primarily Global	Suitable for large structures; low-cost sensors; effective for overall stiffness loss	Low sensitivity to small/local damage; affected by environmental variability
Strain / Displacement-Based SHM	Changes in static or dynamic strain/displacement response	Local to Semi-Global	Directly related to structural behaviour; useful for serviceability and load effects	Requires dense sensor networks for localization; limited spatial coverage
Acoustic Emission (AE) Method	Detection of transient elastic waves from active damage processes	Highly Local	Very sensitive to crack initiation and growth; real-time damage activity monitoring	Difficult source localization in large structures; sensitive to noise
Ultrasonic / Guided-Wave SHM	Wave scattering, reflection, and attenuation due to defects	Local (with imaging capability)	High sensitivity to small cracks; good localization accuracy	Complex signal interpretation; limited coverage per sensor network
Smart-Materials-Based SHM (PWAS, FBG, self-sensing concrete)	Transduction of mechanical changes into electrical/optical signals	Local to Distributed	Embedded sensing; high sensitivity; enables active and passive monitoring	Environmental sensitivity; durability and calibration challenges
Statistical / Data-Driven (AI/ML) SHM	Deviation from learned "healthy" data patterns	Global to Local (data-dependent)	No need for physics-based model; scalable; effective for complex systems	Requires large, representative datasets; interpretability issues
Model-Based (Analytical / FEM-Based) SHM	Comparison between measured response and model predictions	Global with Local Inference	Physically interpretable; can quantify damage severity; supports prognosis	Model inaccuracies; computational cost; ill-posed inverse problems

10 Research Gaps and Future Directions

- Poor sensitivity of global SHM methods to early and localized damage:* The use of vibration-based and modal identification methods enables evaluators to determine the overall condition of a building. However, these methods fail to detect microcracks and localized damage, especially in systems that exhibit complex behavior and static indeterminacy [9,16].
- Influence of environmental and operational variability on damage detection:* The first sentence states that temperature, humidity, and operational load changes produce substantial effects on modal parameters and sensor responses because these environmental factors create difficulties in detecting damage to the system. There is currently a lack of development in reliable compensation and baseline-free detection methods [10,16].
- Lack of standard benchmarking datasets and validation frameworks:* The absence of publicly available standardised datasets that contain established damage scenarios results in two major problems that prevent researchers from conducting reproducible studies and comparing SHM algorithms between different research works [3,54].
- Data scarcity and imbalance in data-driven and AI-based SHM:* The distribution of damage events, which happen less frequently than normal structural conditions, creates datasets that exhibit extreme imbalance. This limitation affects both the reliability and the ability of machine-learning models used in the study to make predictions about new data [8,54].

- *Limited uncertainty quantification in SHM and ML predictions:* For safety-critical decision-making, many SHM studies offer deterministic damage detection results without confidence boundaries, which is insufficient. Bayesian and probabilistic methods are still not widely used [54].
- *Computational and real-time implementation challenges for large structures:* Large civil structures are continuously monitored, producing enormous amounts of data that make online model update and real-time processing computationally challenging. Reduced-order models and effective algorithms are needed [55].
- *Limited physical interpretability of AI/ML-based SHM methods:* AI-based methods excel at damage identification. The black-box nature of these methods reduces engineering confidence and makes it difficult to implement them in practical settings. The required AI models must be both understandable and based on fundamental scientific principles [14].
- *Insufficient integration of global and local SHM techniques:* All damage mechanisms and scales cannot be addressed through one SHM method. Future studies should concentrate on hybrid global-local monitoring frameworks that incorporate data-driven methods, strain, vibration, and acoustic emission [13].

Conclusion

The review provides an organised synthesis of local and global deterioration-detection methods used for structural health monitoring (SHM) of civil structures. The different strategies have their own advantages and disadvantages, as no single method can provide a comprehensive damage assessment across all damage levels. The hybrid global-local SHM frameworks use advanced data analytics to establish a reliable structural monitoring system that achieves high performance. The current state of civil infrastructure SHM requires additional research to develop systems that possess greater durability and enhanced operational capabilities.

The review of existing literature evaluated eight essential monitoring methods for Structural Health Monitoring, including data-driven, local, and global damage detection methods that assess the structural integrity of civil buildings. Global methods that use vibration and displacement measurements enable users to monitor an entire structure's condition and predict its future behaviour, yet struggle to detect early signs of particular problems. The detection of material and component damage becomes more effective with local methods, which include strain-based sensing, acoustic emission, guided-wave, and ultrasonic technologies, as well as intelligent material-based solutions. The performance of data-driven and artificial intelligence systems depends on three critical elements: data accessibility, data understanding, and data integrity. The research demonstrates that monitoring requirements cannot be met with a single SHM method; integrated monitoring solutions are essential. Future research should focus on developing hybrid global-local systems that manage environmental variability robustly, undergo extensive field testing, and combine explainable AI with digital twins to support dependable infrastructure management based on performance metrics.

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