A Critical Review on Structural Health Monitoring: Definitions, Methods, and Perspectives

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Abstract

The benefits of tracking, identifying, measuring features of interest from structure responses have endless applications for saving cost, time and improving safety. To date, structural health monitoring (SHM) has been extensively applied in several fields, such as aerospace, automotive, and mechanical engineering. However, the focus of this paper is to provide a comprehensive up-to-date review of civil engineering structures such as buildings, bridges, and other infrastructures. For this reason, this article commences with a concise introduction to the fundamental definitions of SHM. The next section presents the general concepts and factors that determine the best strategy to be employed for SHM. Afterward, a thorough review of the most prevalent anomaly detection approaches, from classic techniques to advanced methods, is presented. Subsequently, some popular benchmarks, including laboratory specimens and real structures for validating the proposed methodologies, are demonstrated and discussed. Finally, the advantages and disadvantages of each method are summarized, which can be helpful in future studies.

Keywords: Structural Health Monitoring (SHM); Damage Detection Methods; SHM Benchmarks; Anomaly Detection; Structural Safety; Reliability

1 Introduction

In general, 'damage' is defined as a significant factor influencing the structural behaviour in such a way that leads to degradation in the current or future performance of a structure. Therefore, a clear description of damage requires comparing two distinct conditions of a structure: the status of being either 'healthy' or 'damaged'(1). The former describes the base or 'healthy' condition of the structure, and the latter indicates the current or the deteriorated state. As a definition, a healthy structure functions efficiently and preserves its integrity throughout its lifetime (2). On the other hand, in the field of structural identification, damage is associated with changes first in the material and then in the geometry and topology of the structure, e.g., changes to the boundary conditions and connections (3).

Existing techniques for identifying damage cover a wide range, from conventional inspection methods carried out by experts to cutting-edge automated techniques using smart sensors and Artificial Intelligence (AI). The latter identification procedure integrates different fields, namely computer science, data science, electronics, mechanics, material sciences, and civil engineering, which shape the foundation of the interdisciplinary field called Structural Health Monitoring (SHM).

From a general perspective, monitoring the response of structures and detecting probable damages to enhance their performance level and reduce upkeep costs are considered the prime target in SHM. Consequently, structures that benefit from an SHM system commonly experience prolonged service life. In contrast, those that have no such system in place face notably higher risks of structural failures. SHM also guarantees the system's integrity to some extent and can prevent possible failures in the future by sounding a pre-emtive alarm regarding abnormal behaviors.

Over the past two decades, a wide array of inspection approaches have been examined, developed, and established by scientists and engineers to identify, locate, and assess different types of damage. Accordingly, researchers have published many papers to shed light on the fundamentals and applications of those methods. Herein, the authors have attempted to provide a comprehensive perspective on definitions of SHM and damage detection techniques that are described in the following four sections. First, the SHM is defined briefly and its principal objectives are explained. Second, the general concepts within this scope are summarized. In the third part, several damage detection approaches are discussed, and the last section highlights some important SHM benchmarks. Subsequently, conclusions, recommendations, and prospects are provided for future use.

2 Structural Health Monitoring (SHM)

Structural Health Monitoring (SHM) yields precious details regarding a system's behavior by analyzing its responses and evaluating its current mechanical state. A system may include a high-rise building, a bridge, an infrastructure system, or a simple beam. Initially, SHM was employed for damage identification of aircraft in the realm of aerospace engineering and industry. In the late 1970s (4), however, it was implemented to investigate offshore platforms. At the beginning of the 1990s, SHM was extended to civil engineering and infrastructure systems. Just to name some of its applications in this particular field, Beck and Katafyglotis (5) designated a probabilistic identification approach for global health monitoring of a structure by detecting any significant changes in its stiffness distribution. Additionally, Mita (6) presented an overview of the rapidly emerging SHM in Japan's civil engineering in late 1999. In 1997, Al-Khalidy et al. (7) presented one of the earliest studies on the health monitoring of linear systems using wavelets; they discussed the need for promoting SHM for damage detection in infrastructure systems.

With the emergence of new Sensing Technologies, significant breakthroughs in computers, and incorporating structural control methods(8, 9), SHM has expanded extensively in the past two decades. The general idea of SHM can be described through an analogy with the human nervous system (Figure 1) (10). In an intelligent structure embedded with a network of sensors, the sensing function is similar to the nervous system. Also, sensors receive various signals such as vibration, strain, stress, or temperature similar to the human nervous system, which forms a transmission unit that sends different signals to the brain, functioning as a processing and interpretation/diagnostic unit.

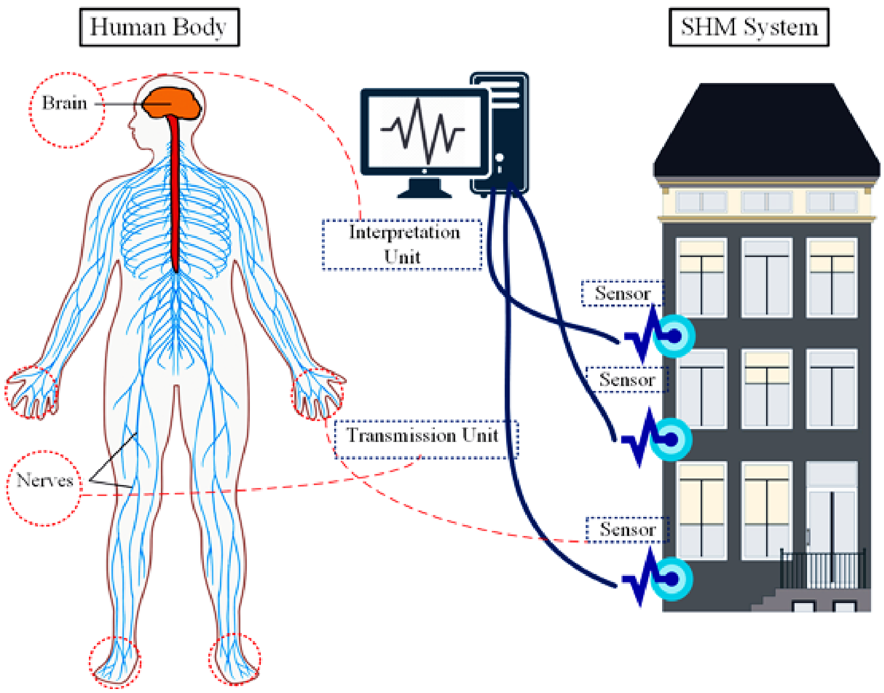


Figure 1 Comparison between the human body and the SHM system (adopted from (10))

By and large, a conventional SHM system consists of three major elements (11):

- Contact or non-contact sensors
- Processing unit (composed of data acquisition, transmission, and storage)
- Data interpretation system (made of diagnostic methods and information management)

Interpretation includes diagnosis (assessment) and prognosis (prediction) of structural changes. The diagnosis notifies the onset of damage, its location, or its severity. This procedure is conducted either by passive diagnosis (i.e., by a passive sensor such as strain gauges) or by active diagnosis (i.e., by an actuator and intelligent sensors) (12). The fusion of these components leads to a fitting SHM system in a particular civil engineering project.

SHM is considered as an inverse problem wherein the structural defects are recognized through the measured data of known inputs. Also, this process is a system identification problem (12). Based on research by Rytter (13), damage identification levels in SHM can be categorized into the following levels according to the extent/scope of the information acquired from the structure:

- **Level 1:** Identification: determining the existence of a defect on a global scale.
- **Level 2:** Localization: determining the location and coordinates of the damage.
- **Level 3:** Assessment: determining the intensity of damage in various components.
- **Level 4:** Lifetime prediction: estimating the structure’s remaining life.

Specifically, the first stage involves monitoring the desired properties of the structure over time, and it provides answers regarding the overall presence of damage in a structure. Comparatively, the second level appears to be more complicated as it requires determining the location of damage and its orientation(12).

In general, the first two levels are defined as diagnosis steps and the next ones as prognosis levels. Importantly, levels 1 and 2 can be evaluated without using any model, but level 3 requires numerical modeling. The last level requires using processes such as breakdown mechanics, fatigue-life analysis, reliability analysis, or structural design assessment (14). In addition, level 4 stems from level 3, wherein the assessment of fracture parameters is utilized to achieve fatigue life analysis to specify the structure's remaining life (12).

It seems that among a large number of publications, a significant portion of studies found in the existing literature is targeted at levels 1-3 (15-17), and relatively small number of papers seek to address level 4 (18, 19). Herein, most of the existing research is concerned with applying damage detection strategies to either laboratory tests or analytical models, not real structures (20). A growing number of researchers have concluded that to assess the risk and the severity of the damage as the necessary information for making a proper decision about the safety of the structure and prevent potential catastrophic failure, there is a need to recognize the type of damage. For instance, in the case of a building under fire, it is crucial to have an SHM system that can detect the severity of existing damage and hence determine if the plan for emergency evacuation is safe to be carried out. Consequently, a new level called 'classification' has been recently presented, aiming to designate the type of damage and bridge the existing gap (21) (See Figure 2).

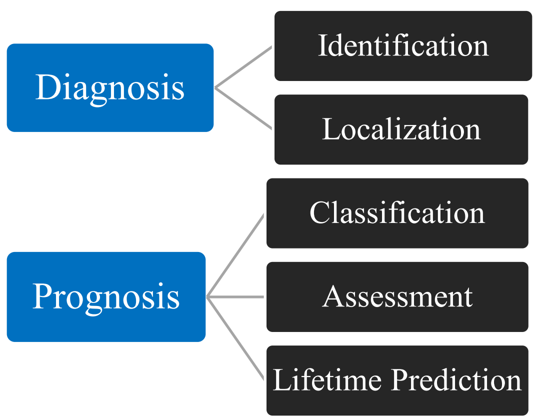


Figure 2 Damage identification levels

3 General Concepts for SHM

The development of a methodology or a technique for structural health monitoring depends on several factors. They include the complexity of the dynamic response, whether the system behaves linearly or nonlinearly, the scale and dimension of the structure, how easily the physical system can be modeled or its behavior be simulated, the nature of the excitation, or how easily a feedback mechanism can be identified to assess the behavior. Some of the crucial factors determining the effective strategy for SHM are depicted in Figure 3 and are elaborated in the following paragraphs.

Figure 3 Common concepts for SHM

3.1 Inspection Scale: Global or Local

According to prior research by Doebling et al. (22), detecting damage is performed by global or local methodologies. Global methods are used to spot the existence of damage and assess the state of the entire structure. In contrast, local methods assist in locating damage or monitoring a specific relevant parameter/metric in the system (23). Visual inspection or non-destructive tests, including ultrasonic, radiography, and acoustic emission, are some practical tools for pinpointing the damage. Since minor faults, such as cracks and delamination, may not show up in global measurements unless they are large, localized measurements are also necessary (24).

Generally, local methods are more common for small and non-complex structures since data is required about the initial state of the structure and such methods designate the vicinity of the damaged member (18). Hence, they are time-consuming and, most likely, quite expensive (25). Consequently, to overcome those limitations, specialists take advantage of global methods, which provide valuable information based on vibration characteristics, such as natural frequencies and mode shapes, especially in complicated structures. Notably, an efficient strategy is applied to identify the structural characteristics of a small area by using global methods, then implementing the local damage assessment methods to zoom in on the damage location (24).

3.2 Response type: Static or Dynamic

A vast majority of damage detection methods are based on assessing the response of the structure due to an excitation source. In this respect, these strategies form two main groups: static response assessment (strain or stress) and dynamic responses (frequencies, mode shapes, or modal damping). Compared to dynamic measurements, measuring static responses is more straightforward but less sensitive to changes resulting from damages (22). Accordingly, using dynamic responses is more efficient for detecting both abrupt and gradual changes, such as detecting deterioration. Nonetheless, dynamic measurement of responses requires controlling environmental and operational effects to attain accurate data. In earlier research in this area, dynamic-based methods relied on frequency measurements., This was principally due to the greater accuracy of devices measuring frequency compared to devices measuring mode shape or geometrical shape. With the advancement of instrumentation, other methods, such as vibration-based methods, were also considered.

Since measuring static responses is more reliable than measuring dynamic ones, some researchers deployed static data in their study cases (displacement and strain) for damage detection (26-30). The occurrence of measurement errors in damage detection data by static response measurement is relatively negligible compared with dynamic responses. While the dynamic matrix requires stiffness, mass, and damping matrixes, the structure's stiffness matrix is solely needed in static concepts. For this reason, static methods generally have simpler equations.

3.3 Behaviour: Linear or nonlinear

The presence of damage induces more complex behavior and causes nonlinear changes. Moreover, damage may cause a structure with a typically linear behaviour to develop nonlinear reactions such as cracking, impacts and/or rattling, delamination, stick/slip, rub, or loosened connections (31, 32). To illustrate these phenomena, Gudmundson (33) proved via experimental tests on a cantilever beam that natural frequencies may increase instead of decline due to breathing phenomena. This behavior confirms the fact that the crack alternately opens and closes during experimental tests. There are different methods for considering nonlinear effects, for instance, nonlinear output frequency response functions (NOFRFs) and/or Higher-Order Frequency Response Functions (HOFRF). In this regard, Sinou (34) classified and reviewed linear and nonlinear methods comprehensively.

3.4 Computation: Model-based or Signal-based

Anomaly identification can be conducted using a model (also called physics-based approaches), or by signal-based methods (also called data-driven approaches). In the former concept, the damage is recognized through tracking variations in the simulated measurements from the structural model (24). Basically, a model is a mathematical abstraction that connects and correlates the input and the output parameters of a structure using (known or assumed) properties (35). In some cases, it requires a post-process response to predict the damage location and severity. For this reason, various mathematical models have been established, such as finite difference methods (FDMs), finite element methods (FEMs), spectral finite element methods (SFEMs), and boundary element methods (BEMs). In particular, FEM is the most widely used approach due to its versatility in modeling of complex geometries (12).

When utilizing the model-based approach, specific parameters of a finite element model simulating the system are updated under the system's responses by studying the dynamic behavior of the FEM model (36-41). Through that process, the FEM model needs to be updated to account for the system changes that occur due to the damage. Model updating includes the optimization of problem solution to seek the optimum set of matrices (mass, stiffness, and damping), leading to the minimization of variances between empirical and computed responses (24). These approaches have some drawbacks because they require prior knowledge of the boundary conditions, damage location, and material properties (14). Moreover, an optimization problem faces challenging issues such as ill-conditioning, which affects the existence, uniqueness, and stability of a solution of an inverse problem, i.e., it is not possible to fully guarantee the determination of the system characteristics based on the given response. Hence, incorporating uncertainty quantification measures such as probabilistic, non-probabilistic, and hybrid methods would be an appropriate alternative (35).

It is also important to point out that FEM methods are not quite suitable when dealing with minor or invisible damages. The preferred mathematical model seems to be relying on wave propagation techniques such as SFEM (42). In contrast, signal-based methods rely on statistical analysis and assess the system's response independently; therefore, they do not require additional information concerning the structure's physical properties and parameters (43-47).

3.5 Feedback: Active or Passive

As for the diagnosis, procedures include two classes; passive and active diagnosis (12). Active schemes excite the structures with a guided-wave (GW) or various ultrasonic waves, Lamb waves, shakers, or piezoelectric transducers (32). Piezoelectric materials and devices can be employed as both actuators and sensors (48).

On the other hand, when measuring input signals is complicated, passive approaches are employed instead. Passive SHM means embedding various types of passive sensors such as stress, strain, loading, environmental condition, or temperature measurement sensors, which are tracked over time, and the collected data is fed back into a structural model. To put it simply, passive SHM systems 'listen' to the responses yet do not engage with the structure, nor does it affect its dynamic behavior (49). A promising passive method is Acoustic Emission (AE), which uncovers acoustic events associated with the occurrence and extension of defects. Other passive techniques include pieces of equipment that are placed in contact with the structure or on the ground to analyze the dynamic response under ambient excitations, such as the dynamic response of a bridge structure under passing traffic or due to wind and ground motions (42).

3.6 Excitation: Forced or Ambient excitation

Dynamic responses of any structure are usually due to two types of excitations; ambient and forced vibrations (50). Ambient excitations are described as stochastic processes such as random white noise. Herein, Random Decrement Technique (RDT) as an effective signal processing method is utilized to measure crosscorrelation functions and free-response decays (51). It is important to note that the use of forced vibration for seismic assessment requires special equipment like eccentric mass shakers to generate the required response magnitude (14). Moreover, using forced vibration testing on existing structures should be done through a well-controlled process as it may cause damage to the structure. Thus, the use of ambient vibration tests as a practical and relatively inexpensive way has increased over the past few years (52-55).

3.7 Domain: Time, Frequency or Time-Frequency

Signal processing techniques have been carried out in different domains, namely time, frequency, or time-frequency domains. Practical vibration analysis begins with acquiring an accurate time-varying signal from vibrometers or accelerometers. Various options and procedures are available to analyze the signal to extract the desired dynamic characteristics that have the potential to illuminate the nature of changes in a structure. Restoring force curves and autoregressive moving average (ARMA) models are a few examples of time-domain methods. In ARMA models, time histories of structural responses are fitted to a model, then the coefficients and residual errors are evaluated as damage-sensitive characteristics.

The most commonly used tool for signal processing in the frequency domain is the Fourier Transform (FT) that takes a real-world time-varying signal and splits it into its harmonic components to deliver information about their amplitude, phase, and frequency. By associating the frequencies with the system characteristics and looking at the amplitudes, it is possible to pinpoint changes caused by incurred damages with relative accuracy. This transformation is carried out using Fast Fourier Transform (FFT) algorithms, which are the most popular ones in practical SHM analyses.

The time-frequency presentation of a signal makes it possible to recognize transient behaviors induced either by damage (desired) or environmental noise (undesired) overlapping within the frequency of the original signal (56). In contrast to FT, abrupt changes due to damages can be identified with the aid of zooming and focusing on the characteristics of wavelets. Wavelet transforms (WTs), Wigner-Ville distribution (WVD), short-time Fourier transform (STFT), pseudo-WVD (PWVD), empirical mode decomposition (EMD) or ensemble empirical mode decomposition (EEMD), as well as Hilbert-Huang transform (HHT) are some of the common approaches (57, 58).

3.8 Solution: Forward (Direct) or Inverse (Indirect)

Parameter estimation solutions, or system identification, are inverse problems since they focus on inverting the standard 'forward' relationship between the parameters and output of a model; the target is to obtain the parameters generating a specific output. Practically, deterministic parameter estimation aims to extract the optimal mathematical model parameters so that the most feasible fit is obtained between the model output and the observed data (35).

4 Traditional Inspection

Traditional inspections can be conducted depending on the value and importance of a structure, repair costs, and failure consequences (12). The most preliminary approach is visual inspections conducted by experienced technical specialists (Figure 4). It is noteworthy to point out, however, that visual inspection is not necessarily the most economical solution. For example, in 2004, bridge inspection expenses were roughly 20M Australian Dollars (AUD) annually in the state of Queensland, Australia (14). Moreover, a visual inspection cannot be practically used in some conventional, especially large and complex structures.

Visual inspection techniques can be combined with different types of experimental tests, which are typically categorized as either destructive testing (DTs), primarily used to determine the material properties, or Non-destructive testing (NDT). NDTs aim to inspect the nature of the damage or control its propagation in a member, joint, or various connections. As a result, NDTs mainly point out the variation of physical values of defects and are deployed for Quality-Control

(QC), material properties determination, and damage detection (59). There are some differences between NDTs and SHM. First, regarding the sensing methodology, in SHM, the sensors are permanent and in fixed positions, while in NDTs, they are brought to the point of investigation. Secondly, some specialists articulate that SHM should be carried out online or in an automated fashion, while NDT is conducted via another inspection (60).

Although using NDTs may seem feasible for inspecting small structures, they have some drawbacks. First, employing these techniques usually involves a temporary interruption of the functionality of the structure. This problem makes them time-consuming and costly. Additionally, on many occasions, due to the inaccessibility or the invisibility of the location of the damaged area for the inspector, it may be difficult or impractical to perform a satisfactory damage inspection (61). Lastly, the characteristics of the material also affect the results. Table 1 summarizes several NDTs and the principal characteristics of the material that should be measured (62).

Overall, these methods are appropriate when the initial information about the vicinity of the failure is available. Likewise, they are not practical if the member is not accessible or is covered by other structural components (14). Accordingly, most of these methods are limited to only simple members such as beams, columns, or plates; and they are not practical in detecting damage in complex structures, such as multi-story buildings or large bridges (63). A list of commonly used non-destructive methods is provided in the ASM Handbook (62).

Table 1. NDTs and their relative material characteristics (62)

Method	Important Characteristics
Liquid penetrant	Defects must intercept surface
Magnetic particle	Requiring magnetic materials
Eddy current	Requiring conductive or magnetic materials
Radiography and x-ray	Changes in thickness, density, or elemental composition
Neutron radiography	Changes in thickness, density, or elemental composition
Optical holography	Surface optical properties

Figure 4 Visual inspection on a bridge girder (64)

5 Anomaly Detection Methods

The SHM literature shows six commonly used structural assessment methods (Figure 5), namely, response-based techniques, reliability-based methods, Acoustic Emission (AE), feature extraction methods, computer vision, and machine learning in data-driven methods. In the following, each technique and its subcategories are described, and relevant papers are reviewed.

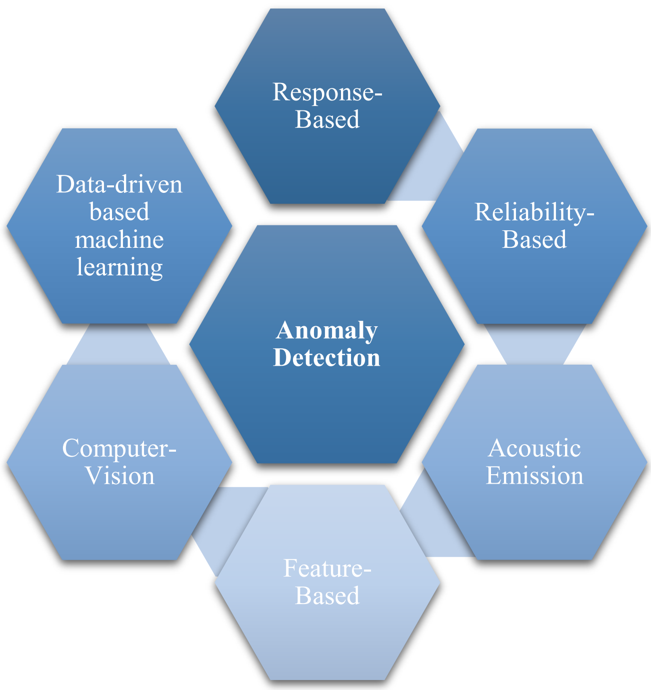


Figure 5 Anomaly detection approaches in SHM

5.1 Response-Based Techniques

5.1.1 Displacement-based approach

Measuring static responses is easier and more reliable in comparison with dynamic response measurements. Therefore it is the interest of a large proportion of researchers. For example, Xu et al. (65) deployed non-contact laser displacement sensors to measure dynamic displacements on a frame structure model, searching for baseline states and joint connection defects. They utilized displacement time series with two neural networks to find damage and assess its extent.

Huang et al. (66) proposed a displacement-based damage assessment method that utilized nodal displacements on a steel beam that combined analytical and numerical models with some experiments. Their methodology was practical since it required a few sensors, and there was no need to have a baseline condition assessment of the structure.

Ono et al. (67) used influence lines of the road to detect damage on a full-scale finite element bridge slab. Different parameters, such as damaged positions and boundary conditions, were examined to investigate their impacts on the performance of the presented methodology.

Huseynov et al. (68) studied numerical analysis to find an index on the basis of rotation measurements. To this end, they proposed a sensitive index using the difference in rotation influence lines of damage and healthy states. It was concluded that this parameter could successfully identify damages on an experimental bridge model.

5.1.2 Strain-based approach

Monitoring strain is possible by employing Fiber-optic strain gauges, Fiber Bragg grating (FBG) sensors, and piezoresistive sensors such as microelectromechanical systems (MEMS) (69, 70). Usually, a large number of sensors are needed for measuring strain because the strain is a localized quantity. Thus, piezoelectric polymers, polyvinylidene fluoride (PVDF) patches (71, 72) are more recent tools that are suggested to measure strain (32).

Jang et al. (73) employed the damage locating vector (DLV) method with static strain measurements to localize damage on 2D and 3D planar truss models. It was shown that the proposed method required fewer strain sensors without needing to measure the damaged members. In this context, Zhao et al. (74) introduced the basic theory of modal macro strain-based using long gauge distributed sensing technology and deep learning theory for the first time.

Rageh et al. (75) utilized strain outputs induced by unknown, nonstationary external inputs on a steel railway bridge. A coupled Proper Orthogonal Modes (POM) and ANN methodology were used to assess stringer–floor beam connection deterioration on the bridge in a noisy environment.

5.1.3 Vibration-based methods

Structures are subjected to a variety of loading types during their lifetime. Forced or ambient vibrations might generate these excitations. Regardless of the type of excitation, when the vibratory motion threshold exceeds a certain level, it might cause damages such as structural fatigue damage, cracks, strength or stiffness degradation, and other types of deformations. Environmental loads may also induce noise, which adversely affects the signals (76). Ambient excitations seem less risky and may not cause severe damage. Furthermore, the evaluation of structural response under ambient excitations is more straightforward.

The response of a system is related to its inherent dynamic characteristic, namely inertia (mass), damping, and stiffness. These dynamic characteristics are unique for each structure and can change as a result of damage. Accordingly, any structural damage can be traced and correlated with the subsequent changes in these dynamic structural characteristics (stiffness, mass, or energy dissipation). In that case, changes in natural frequencies, mode shapes, and damping properties inherently related to stiffness, mass, and damping indicate the incurred structural damages (14, 77). Vibration-based methods aim to incorporate and integrate the experimental vibration data, e.g., acceleration, velocity, or displacement, with vibration models for damage evaluation and develop damage models for prediction. These models range from pure lumped parameter models to complex finite element models (32).

It is important to note that the low-frequency examination carried out by these techniques typically involves the structural components throughout, along with boundary conditions. Consequently, these methodologies usually are considered global diagnostic tools (12). Therefore, they are commonly integrated with the sensitivity of local tools such as Scanning Laser Doppler

Vibrometers (SLDVs), guided waves, or Ultrasonic methods with the frequency range of kHz to MHZ. A summary review of vibration-based methods can be found in (35, 78, 79). In the following sub-sections, the most commonly used vibration-based, namely Modal Based approaches, are discussed.

5.1.3.1 Natural frequencies

Monitoring changes of natural frequencies was among the earliest work carried out by researchers for damage detection, and numerous attempts have been made in this regard (32). Generally, frequency-based techniques are based on the fact that when a structure undergoes any type of damage, this damage results in a change in the structure's natural frequencies. These approaches are practical and helpful only when a global assessment is needed.

Tracing shifts of frequencies cannot provide detailed information about damage characteristics (80, 81). Therefore, techniques solely dependent on changes in frequency are usually limited to the first level of damage identification and, as stated, are considered as global detection methods. What's more, most frequency-based techniques, which can identify and localize defects, are heavily dependent on the existence of a precise FEM model of the actual structure (82). Furthermore, frequency information by itself is not practical since several combinations of damage phenomena, such as cracks in different locations, can produce the same changes in the natural frequencies (20). Hence, the implementation of natural frequencies as the sole technique for anomaly identification can lead to unrealistic damage assessments and evaluations (83).

Many researchers have deployed frequency approaches on simple structures like beams or plates (84-88). For instance, Kim et al. (89) compared frequency-based damage detection (FBDD) vs. mode-shape-based damage detection (MBDD) on a simple beam and two sets of modal parameters. They concluded that through FBDD, the damage could be identified with a much smaller error, and by applying the MBDD, the damage could be located more accurately. More recently, Nguyen et al. (90) employed a vector of first few frequencies as the multivariate input of a statistical distance-based damage identification study using experimental data from two real benchmark structures.

Mohan et al. (91) designated a frequency change correlation for detecting damage in a cantilever beam. They studied four different damage scenarios and located the corresponding damages by Damage Location Assurance Criterion (DLAC), based on Modal Assurance Criterion (MAC) established by Messina et al. (92). The DLAC measures the correlation of a vector of experimental natural frequency change ratios instead of mode shapes (23). However, few researchers have applied the frequency method to complex structures such as space frame structures (93). In order to cope with the obstacles mentioned above, research studies have exhibited inclinations towards concentrating on the implementation of mode shapes (94-96) and derivatives (97) since changes in these parameters are more sensitive to local damage than changes in natural frequencies (98). A concise review of these methods is noted in (99, 100).

5.1.3.2 Mode-shapes

Measuring mode shapes is more laborious than measuring frequencies, and also, a significant number of sensors is required to specify mode shape vectors accurately (101). This technique typically utilizes mode shapes and compares the measured mode shapes either directly or the various features of mode shapes, such as curvature or modal strain energy, to improve the sensitivity (20). The occurrence of singularities in the mode shape due to the existence of defects is the critical factor that reveals damage. In other words, the higher the extent of damage, the more singularities in the mode shape (102).

Mode shape methods primarily required both data from the intact and damaged structure. The baseline data is obtained from either an experimental test or a finite element analysis. Broadly, these methods are sensitive only to limited areas within a structure (e.g., mid-span of a clamped beam), and the reported work in this area has been mainly limited to laboratory experiments. Furthermore, reported cases indicate that the approach has been more effective for preliminary damage localization than more accurate localization (103).

Nevertheless, recently developed model-based methods have shown promising prospects for either mode shape data or mode shape changes identification of damaged structures. The most popular technique in this regard is MAC (104-107), a statistical index that is more sensitive to substantial variations while relatively insensitive to slight differences in the mode shapes, taking values between 0 (i.e., uncorrelated) and 1 (i.e., perfect correlation). Values larger than 0.9 indicate correspondence, whereas small values signify low similarity between the two shapes. (108). Some of the popular mode shape-based techniques are compiled in (100, 109).

5.1.3.3 Modal curvature

Derivatives of mode shapes appear more sensitive to defects since the reduction in stiffness causes an abrupt change in the mode shape’s first or second derivatives (slope, curvature, or strain) (25, 110). In short, occurrence of damage leads to a decline in stiffness that subsequently causes an increase in curvature. Thus, damage identification is performed by comparing differences in the pre and post-damage curvature mode shapes near the vicinity of the damaged region. This procedure implements multiple modes and is summed up in a damage parameter for a particular location (23).

Pandey et al. (111) presented mode shape curvature methods for detecting and localizing damage in a cantilever and a simply supported beam. They employed a central difference estimation to derive the curvature mode shapes from the displacement mode shapes using a numerical equation. It was concluded that changes in the displacement of mode shapes were unable to locate the damage region. In addition, it was proved that MAC and coordinate modal assurance criteria (COMAC) were not sensitive enough for detecting slighter damages.

Wahab et al. (112) confirmed that detection is possible using multiple modes in the case of multiple damages. Therefore, they presented the Curvature Damage Factor (CFD), providing clear identification of multiple damages occurring and using classical mode shape curvature obtained from only one mode. They also applied modal curvature techniques to measured data on a concrete bridge and achieved promising results in terms of damage identification and localization. In addition, by using measured data on the aforementioned bridge, it was demonstrated that the modal curvatures of the lower modes were more precise compared to those of the higher ones.

Roy and Chaudhuri (113) found that variation in the fundamental mode shape and derivatives were associated with the location of the defect. Thereby, mode shapes might not indicate damage in contrast with mode shape derivatives in some cases. Roy (114) put forward a robust localization technique through the derivatives of mode shapes related to undamaged and damaged states of a structure. He noted that the difference in mode shape slopes resulted in a Dirac delta function for damage location. It was observed that the difference in mode shape curvature was discontinuous at the position of the defect. Accordingly, that approach was effective in identifying and localizing damage due to slight changes despite the existence of noise-contaminated data.

Janeliukstis et al.(115) developed a square curvature procedure to measure the damage on pre-stressed railway sleepers. Although their method revealed efficiency in detecting damage on the mid-span of the rail, no accuracy was noted in finding damages on the edges. The effects of environmental conditions, including temperature and humanity, on the dynamic properties (natural frequencies, mode shapes, and mode shape curvature) for a wind turbine blade were investigated by Ou et al. (116). The authors offered thorough documentation regarding the configuration of the experimental benchmark, sensor types, and the nature of excitations.

5.1.3.4 Modal strain energy

Shi et al. (117) proposed Modal Strain Energy (MSE) in damage localization for the first time. Therein, Modal Strain Energy Change Ratio (MSECR) was established as an indicator of damage location. This approach was verified through a numerical model and an experimental specimen with a two-story portal steel frame. The results revealed that the method was efficient in the single damage quantification with a 7% noise. However, in the case of multiple damages, results were not satisfactory at the same noise level.

Cornwell et al. (118) implemented a strain energy approach on a beam and a plate. The authors proposed fractional strain energy for the healthy and damaged beam, which required the structure's mode shapes in damage and baseline condition. Although this approach showed some errors near the nodes, it was advantageous while using ambient excitation. In addition, the algorithm was able to locate even slightly damaged areas employing a few modes. Hu et al. (119) extended the previous work by developing a non-iterative exact solution methodology called cross-modal strain energy (CMSE), which used only a few modes of damaged structure for estimating damage severity. The method was verified on a three-dimensional five-story structure by assessing single-damage and multiple-damage scenarios under an ordinary noise environment. In a recent study, Nguyen et al. (120) proposed a correlation method using change in the ratio of modal strain energy to eigenvalue directly estimated from the experimental modal information, which is powered by a sensitivity-weighted search space scheme incorporated with genetic algorithm to overcome the ill-posed problem that causes false detection errors. The improved method is shown to be effective in locating and assessing damage in a complex steel truss structure.

Wahalathantri et al. (121) proposed a modification function according to mode shape curvature, which could enhance the previous approach and qualify damage to some extent. Tan et al. (122) presented a modal strain energy damage index as the input of an Artificial Neural Network (ANN). This method simply used the first mode of vibration and was preferable in detecting, locating, and quantifying single and multiple damage scenarios on steel beams. In an effort to extend to large-scale building structures, Wang et al. (123) proposed a component-based MSE damage index method and combined it with the modal flexibility method to locate damage in three-dimensional asymmetrical building frames. On the side of bridges, Jayasundara et al. (124) studied modified modal flexibility and strain energy indices as the input of an ANN to assess deficiencies on full-scale arch-type bridges. The proposed strategy was promising, even in the presence of noise-contaminated data along with the accumulation of multiple damages. The modified indices are formulated by decomposing the traditional modal flexibility and strain energy into vertical and lateral indices, extracting the larger values for each type and normalizing them to get a fix on the location of the damage very effectively (125).

5.1.3.5 Damping

Arising damage in a structure can cause an increase in damping. However, this structural characteristic is not sensitive enough to indicate damage. As a case in point, Hearn and Testa (126) explored the use of modal parameters, including frequency, mode shape, and damping values, for detecting damages in a welded steel frame subjected to cyclic load. It was observed that after the accumulation of damage, the damping level might decrease due to cumulative deterioration.

Salawu and Williams (127) conducted a full-scale test on a concrete bridge prior to repairing actions. It was demonstrated that the repairs led to a slight change in the natural frequencies, but no identifiable trend could be established in the modal damping ratio.

Frizzarin et al. (128) recommended applying the nonlinear damping ratio as a damage index for reinforced concrete structures. By that, they were able to identify anomalies without any reference to the baseline condition. Moreover, they observed a significant correlation between the increase in the nonlinear damping and a decrease in the structural stiffness connected with the escalation in seismic damage intensity.

Montalvão et al. (129) developed a modal damping factor to identify delamination on composite materials such as Carbon Fiber Reinforced Plastics (CFRP). This low-cost method required either FEM or experimentally measured mode shapes and presented a geometrical probability definition of the damage vicinity for any bi-dimensional structure. Similar researches on the application of damping ratio as a damage index are compiled in (130, 131).

5.1.3.6 Frequency response functions (FRFs)

In essence, a frequency response function is defined as a mathematical representation between input and output of a system derived from the Fourier transform (132). Having the general equation of motion, the displacement response in the frequency domain is given by

$$\mathrm{X}(\omega) = (-\omega^2\mathrm{M} + \mathrm{j}\omega\mathrm{C} + \mathrm{K})^{-1}\mathrm{F}(\omega) = \mathrm{H_d}(\omega)\mathrm{F}(\omega) \tag{1}$$

$$\dot{\mathrm{X}}(\omega) = \omega\mathrm{X}(\omega) = \mathrm{H_v}(\omega)\mathrm{F}(\omega) \tag{2}$$

$$\ddot{X}(\omega) = -\omega^2 X(\omega) = H_a(\omega)F(\omega) \tag{3}$$

where $H_d(\omega)$ indicates the displacement Frequency Response Function (FRF) matrix and $j = \sqrt{-1}$ (132). FRFs require installing a smaller number of sensors, and the corresponding measurements efficiently fulfill local detection (133). Among the different dynamic characteristics of the structure, it is relatively easier to obtain the structure's frequency response. Furthermore, since these data can be, for instance, derived from seismic tests on a structure, FRFs express the actual behavior of the structure and can be more reliable. Consequently, different FRF-based damage detection techniques can be obtained using displacement frequency response (DFRF), velocity frequency response (VFRF), or acceleration frequency response (AFRF), as presented by equations (1-3) (134).

Esfandiari et al. (135, 136) established an FRF-based parameter assessment approach using incomplete measured responses derived through a quasi-linear sensitivity equation. To cater to this need (employing incomplete measurements in the derivation of the sensitivity equation), they proposed an approximation of the damaged structure's transfer function via the measured frequencies coupled with modal damping ratios of the damaged structure and the analytical mode shapes of the healthy structure. Likewise, numerical simulations were adopted to validate the robustness of the model updating for extended damage scenarios through highly noise-contaminated data. The authors also formulated methodologies in terms of picking subsets of measured responses and suitable weighting of sensitivity equations. Staszewski and Wallace (137) concluded that the wavelet ridge algorithm could effectively derive and visualize data out of wavelet-based FRFs.

Bandara et al. (138) used DFRF along with an ANN pattern recognition for localization and quantification of damage in a frame. In that research, the authors deployed a finite element model of a two-story frame structure to train the neural network, which could identify even slight damages with reasonable accuracy under 10% noise. Liu-Sheng and Jun (139) used AFRF for detecting and localization of damage in a planar truss. They demonstrated that the method made accurate predictions about the damaged member but could not exclude the damage probability of circumference members.

The accuracy of FRF methods depends on using raw data in measuring frequencies. However, a massive amount of data leads to more significant data processing demands. To deal with this problem, data compressing methods such as fuzzy clustering algorithms or principal component analysis (PCA) could be practical in this scope. Data compression methods can also reduce environmental effects (140, 141). Moreover, in a complex structure, variations in natural frequencies are the same for both damaged and undamaged cases (141). Hence, the solution is reading damage and healthy data simultaneously (142).

5.1.3.7 Matrix-based (stiffness and flexibility)

Changing the stiffness and flexibility matrices induced by damage and comparing them with the undamaged state devises another damage identification strategy. Zimmerman and Kaouk (143) considered damage as changes in stiffness using an eigenvalue problem derived from a general equation of motion for a finite element model. Sivico et al. (144) proposed a method considering changes in stiffness and damping parameters in the time domain. It was observed that higher modes contribute more than lower ones to the structure stiffness (145, 146). Accordingly, a precise estimation of the stiffness matrix needs to measure all modes of the structure. However, measuring higher frequencies is quite tricky due to the apparent limitations of the experimental apparatus. To this end, the flexibility matrix method was proposed for estimating the changes in system stiffness by means of first mode shapes and modal frequencies, which have the most significant influences on the structure's response (147). In this aspect, Pandey and Biswas (147) developed a novel algorithm that was capable of localizing damage in three types of beams using the first several modes and measuring flexibility changes. Reich and Park (148) utilized strain-based sub-structural flexibility matrices for detecting damage in a reinforced concrete model.

Park et al. (149) compared the predicted position of damage obtained via damage index methods with visual inspection results in a reinforced concrete box-girder bridge. They proved that environmental conditions, such as the atmospheric moisture and the dry summer months in the region, could affect the damage index results.

Tomaszewska (150) attempted to detect damage on a simple beam and a FEM model of a real-world tower through structural flexibility and mode shape curvature. He tested the modal identification errors by an absolute damage index. It was pointed that ignoring modal errors in the damage detection process could distort results. Additionally, using the flexibility and curvature indices improved the accuracy of detection when erroneous modal data was collected.

Grande and Imbimbo (151) put forward a new technique by combining the classical flexibility method and a multi-stage procedure relying on Dempster's rule discussed in (152, 153). That approach was applied to two case studies, including a fixed-end beam and a three-dimensional structure benchmark model. Overall, the method effectively detected damage in both cases, even with a limited number of parameters and noise measurements.

Wickramasinghe et al. (154) confirmed the applicability of modal flexibility to detect and locate single, multiple, and complex damage scenarios. The authors developed two damage indices that used only the first four modes to detect defects on a real suspension bridge simulated using a FEM.

5.2 Reliability-based Methods

Engineers have always tended to use SHM for optimizing the cost of maintenance based on the remaining service life of a structure. However, numerous uncertainties exist in current procedures. Thus, to consider these uncertainties, a probabilistic approach, such as reliability-based methods, is used to overcome existing gaps. Many researchers have developed reliability-based methods as a quantitative tool to scan the health state of the structure for deterioration or damage (17, 155-157)

Soyoz et al. (158) deployed structural parameters, stiffness, and damping values according to seismic response measurements obtained from shaking table tests as indexes. Some scholars have also introduced a probability-based framework for estimating the performance of the structure. Others developed reliability-based assessment methods using strain-monitoring data to develop deterioration indices (159, 160). Notably, those methods have also been investigated for damage detection in various infrastructures (17, 161-163). Nonetheless, some limitations cast doubts on practical implementation (164). A large number of methods mentioned above that are based on the reliability approach have solely utilized strain as input data (159, 160). Strain measurements have some drawbacks; for instance, they might not be stable, especially over a long time. This approach may also be expensive and require complex signal processing systems (165).

In addition, recent studies have revealed that reliability-based procedures are prone to an inaccurate estimation of the structural failure probability due to the sensitivity of the results to the accuracy of the input data and require making assumptions for numerous input parameters (165, 166).

5.3 Acoustic Emission (AE)

Acoustic emission (AE) has been studied as a non-destructive evaluation (NDE) and structural health monitoring method over the last six decades (167). It is defined as propagating transient elastic waves in the materials, which are generally propagated from internal energy sources due to damage initiation (168). The primary components consist of the structure, AE sensors, amplifiers, acquisition, and recording unit coupled with the data processing system (169). Signal characteristics that are commonly utilized include rise time, peak frequency (PF) or average frequency (AF), duration, and ringdown count (4).

In practice, AE is helpful for global monitoring, real-time assessment, and remote monitoring to discriminate different sources of damages (170). AE has been deployed broadly to assess fracture mechanisms and characterize structural damages, especially for composite materials and for complex damage mechanisms such as matrix cracking, delamination, fiber fracture, pull-out, and gross material faults (171). Moreover, a large percentage of the papers that have reported this approach concern concrete material and structures (172).

Hamdi et al. (173) introduced a real-time method through random AE signals obtained from a static bending test on a cross-ply Glass Fiber Reinforced Plastic (GFRP) composite material. They concluded that the Hilbert–Huang transform (HHT) was efficient for nonstationary AE signals feature extraction. Moreover, instant frequencies could provide applicable descriptors in terms of in-situ health monitoring.

Behnia et al. (168) investigated steel fiber reinforced concrete beams under pure torsional loading to find different damage mechanisms, including micro and macro-cracking and fiber tension softening. They introduced an unsupervised pattern recognition approach and a novel technique, referred to as Spatial Intelligent b-value Analysis, to quantify fault levels for each loading state. Some practical reviews regarding AE damage detection are available in (169, 174, 175)

5.4 Feature-Based

The analysis of measured signals searching to reveal hidden features related to the structure's condition has recently attracted a lot of interest. Signal processing techniques derive features from time, frequency, or time-frequency (176). Some of the most practical tools for extracting information from each domain are presented in the following sub-sections.

5.4.1 Time-domain

Time series is a statistical tool for creating mathematical models that simulate the dynamic characteristics using measured data, divided into two categories, namely parametric and nonparametric time series. In the first group, the observation is simulated using nonparametric time series such as frequency response function (FRF), binned power spectral density (PSD), etc. In this approach, dynamic variations caused by damage are recognized through changes in statistical parameter characteristics (14). In the second group, the input-output relationship of a system is presented through an Average model with exogenous inputs (ARMAX) with the following equation:

$$A(q)y(t) = B(q)u(t) + D(q)\varepsilon(t) \tag{4}$$

where $y(t)$ denotes the response of the system to the input excitation $u(t)$ and $\varepsilon(t)$ is the residual term. The terms A, B , and C are the coefficients or parameters in polynomials with the delay operator q. The polynomial order defines the time-series model order, which is an unknown term and is determined through different techniques, namely Akaike's information criterion (AIC), Minimum description length (MDL), Root Mean Squared Error (RMSE), and best model order (BMO) (14)(177). Skewness, crest factor, kurtosis analysis, and RMS amplitudes are some of the popular features that apply to time series (178).

In a general sense, changes in a system lead to changes in the coefficients and residuals of the time series, which form the main criteria for damage diagnosis in the parametric time series. Since measuring input vibrations is challenging, and it is costly to apply this approach to real-world structures, output-only time-series, which utilize ambient excitation, are more desirable and practical. Thus, various types of output-only parametric time-series have been established in the realm of SHM, including but not limited to AR, ARMA, Vector Autoregressive (VAR), and Vector Autoregressive Moving Average (VARMA) (14).

Monavari et al. (179) proposed a signal-based approach utilizing autoregressive (AR) time-series residuals. In this paper, a novel AR model order estimation algorithm was established that was capable of enhancing the sensitivity of the AR model prediction concerning deterioration. As a result, the authors were successful in qualifying slight changes like deterioration on a high-rise FEM concrete building excited by real ambient excitations. AR model residuals can also be combined with test statistics such as the *T*-values of statistical hypothesis of chi-square variance test to locate crack-induced deterioration in a complex lab test of a box girder structure (54)

Time series is one of the tools implemented in statistical pattern recognition applications for SHM (180). Since the method is based on a partial structural dynamics model, it can identify even a small number of variations (181). As an illustration, Gharehbaghi et al. (55) employed AR time-series along with a robust algorithm that was able to select sensitive uncorrelated features. Afterward, they established a pattern, which they then employed in a super vector machine (SVM) algorithm to classify different deterioration scenarios within an analytical model. Following this approach, they could locate and qualify deterioration under the effect of environmental variabilities, such as high noise and operational errors.

5.4.2 Frequency-domain

Fourier spectra, cepstrum analysis, difference frequency analysis, and the high-frequency resonance technique are appropriate tools for damage identification, especially for gear faults and roller bearings (182). Fourier transform (FT) and fast Fourier transform (FFT) are considered the principal anomaly detection concepts. As a case in point, in a study conducted by Melhem and Kim (183), FFT and CWT were compared for detecting damage in real prestressed concrete beams and concrete slabs. Results proved that FFT could identify the progression of damage in the beam but not in the slab. Contrarily, CWT could differentiate the initial and damaged states for both structures.

Ngo et al. (184) developed an FFT-based correlation coefficient approach to evaluate damages on a beam and bridge. It was deduced that FFT used fewer calculation steps than FT, and the proposed method could locate structural decline through crosscorrelation matrices.

5.4.3 Time-Frequency domain

The time-frequency presentation of a signal allows for the recognition of transient behaviors induced either by damage (desired) or environmental noise (undesired) overlapping with frequency within the original signal (56). The capability of wavelets through multi-scale analysis of transient events induced by damage (desired) or environmental noise (undesired) generated considerable attention for SHM. In contrast to Fourier Transform, wavelet analysis can describe any type of signal both in time and frequency domain simultaneously, while FT can map a signal from the time domain to the frequency domain. Moreover, through a flexible window location and scale, wavelets can identify abrupt changes due to damage with the aid of zooming and focusing. This can be achieved through multiresolution analysis (MRA) from discrete wavelet transform (DWT) and Wavelet packet transform (WPT) or the wavelet spectra from continuous wavelet transform (CWT) (58, 185).

Noori et al. (186) applied data obtained via long-gage FBG strain sensors into a modified wavelet packet energy rate index to quantify damage in a steel bridge under a noisy environment. Zhao et al. (187) used the structural mode shapes extracted from the finite element model of a simply supported reinforced concrete beam that is employed for damage identification using different types of wavelets. They concluded that the maximum curve reaches a peak value at a specific scale for a specific case, based upon which a new mode shape-based algorithm and damage index were proposed for damage identification. Haq et al. (188) investigated the use of DWT and CWT for Fatigue damage mounting and estimating the residual life of RC frames.

Huang et al. (189) established a new local and adaptive method for analyzing stationary and nonstationary signals called the Hilbert–Huang transform (HHT). HHT relies on empirical mode decomposition (EMD) and can decompose the original signals into a series of basic functions and almost mono-component called implicit mode functions (IMFs). Through IMFs, one can identify all the instantaneous frequencies, which are then utilized to calculate the Hilbert spectrum and enlighten distinctive chrematistics of the original signal (190). Sanchez et al. used empirical wavelet transform and HHT to calculate the three structures' natural frequencies and damping ratios (191).

Yang et al. (192) proposed a modified EMD for the identification of modal parameters on a four-story steel frame. AE signals of 3D braiding composite shafts under tensile and torsion were analyzed by HHT in (193). It was shown that HHT could do modal separation of AE signals to identify matrix damage types on composite materials.

Babajanian et al. (176) analyzed cable-bridge responses and extracted features using STFT. A support vector machine (SVM) and a filter-method approach called 'ReliefF' were used to find the sensitive subset of features for detecting damage.

5.5 Computer Vision

Computer vision is a sub-set of artificial intelligence that tries to derive information from digital data, including images or videos, by pairing computers and machines (194). The ultimate target of this methodology is to automatically convert the image or video data into inferable information (195). Computer vision consists of a vision system, a computer, and an image processing software platform (see Figure 6) (196). Vision sensors typically include digital cameras, smartphones, infrared cameras, optical lenses, and laser scanners. In addition, image acquisition utilizes customary cameras, camera tracking vehicles, and robotic systems such as UAVs and drones. In this regard, displacement, temperature field distribution, and superficial defects are the most common data recorded by non-contact vision cameras. The processing unit includes image processing techniques that extract features from digital data. In this regard, various types of low-level and high-level features such as shape, texture lines, pixel intensity are utilized in image processing algorithms.

Computer vision is mainly deployed for assessing damages on surfaces and visible parts of structures, including different types of cracks, steel corrosion, or concrete spalling. It consists of two main groups, including image processing-based and deep learning-based approaches. Various image/video processing techniques that use features extracted from acquired images are utilized regarding the first group. These consist of edge detection filters (197, 198), morphological features (199), and bottom-hat transform (200). Herein, different machine learning classification methods are used, such as SVMs, Naive-Bayes, and K-Nearest Neighbors (KNN). Moreover, in the case of big data, deep learning techniques can be applied to image features.

With respect to the first group, Shan et al. (201) used two cameras to retrieve coordinates of the crack edge using the Canny-Zernike algorithm. The width of the crack was identified via a minimal edge detection approach. Qiang et al. (202) proposed an adaptive canny edge detection algorithm for crack identification using a Gauss filter and Otsu method. They segmented cracks from the background by applying an iterative threshold algorithm. Sari et al. (203) classified and segmented asphalt pavements by deploying the SVM and Otsu methods, respectively. Some of the popular crack detection algorithms are reviewed in (204).

Motion magnification is another trending technique that deploys high-speed cameras to amplify small displacements and lead to model identification in structures. As a case in point, Chen et al. (205) calculated the mode-shaped curvature of a beam to identify damage. Accelerometer and laser vibrometer measurements were deployed for validation of the technique. In a paper by Sarrafi et al. (206), phase-based motion estimation (PME) and video motion magnification were employed to perform operational analysis on a wind turbine blade and extract resonant frequencies and operating deflections. A single camera captured the sequential images, and the MAC criterion detected damage scenarios applied to the blade. It was concluded that the use of phase-based motion could be efficient in a noisy environment. PME was applied on a laboratory and real bridge by Cabo et al. (207). The results indicated that PME had a good performance in comparison to traditional sensing methods (e.g., LVDT). Furthermore, natural frequencies are not enough for classifying damage, and other information regarding mode shapes is required.

Regarding the learning-based methods, it should be noted that they have broadly improved the first group's ability via different detection approaches, including image classification, object detection, and semantic segmentation (195). Furthermore, thanks to the rapid developments of technology, graphics processing units (GPUs) paired with Field Programmable Gate Arrays (FPGAs) as fine-grained programmable devices are the most suitable platforms for implementing convolutional neural networks (CNNs) since they offer super performance for the sake of pure computation (194).

German et al. (208) proposed a damage index for concrete columns to quantify the damage, such as cracks and spalling, based on computer vision for rapid inspection after earthquakes. Chen et al. (209) used aerial images captured by UAVs to evaluate the degrees of damage to buildings after earthquakes. Various image texture features were used to identify ground targets (building, road, mountain, riverway, and vegetation). An SVM classifier was used to evaluate the extent of the damage, and a new damage degree evaluation (DDE) index to identify the damage potential and intensity of the earthquake was devised..

Zhang et al. (210) established a CNN called CrackNet, able to classify different cracks on 3D asphalt surfaces, with the explicit objective of pixel-perfect accuracy. For training, two GPU devices were deployed on 1800 images of asphalts.

Liang (211) exploited deep learning and Bayesian optimization by examining a reinforced concrete (RC) bridge after an earthquake on three sequential stages, including the system stage, component stage, and damage localization. Yang et al. (212) deployed thermal imaging to combine a rolling electric heating rod with a horizontal thermal excitation methodology to generate a temperature gradient on the side of the crack. An improved Fast R-CNN was implemented to learn temperature gradient and to detect cracks of different depths on a steel plate.

Oudah and El-Hacha (213) conducted damage and deformation evaluation of a large-scale that was tested on two new RC connection systems using digital image correlation (DIC). Ni et al. (214) proposed a deep-learning-enabled data compression and reconstruction framework, divided into two phases: (a) a one-dimensional CNN; (b) a new SHM data compression and reconstruction method based on Autoencoder structure. To validate the approach, acceleration data from the SHM system of a long-span bridge in China was employed. In the abnormal data detection phase, the results showed that the proposed method could detect anomalies with high accuracy.

Chen and Jahanshahi (215) proposed a method for detecting cracks on the pixel level. In this study, a rotation-invariant fully convolutional network (FCN) called ARF-Crack was established that explicitly used the rotation-invariant characteristic of cracks. The architecture of the FCN named DeepCrack for pixel-level crack detection was adopted and revised where active rotating filters (ARFs) were utilized for encoding the rotation-invariant characteristic into the network.

Comprehensive reviews on new advances and computer vision applications for SHM are available in (195, 196).

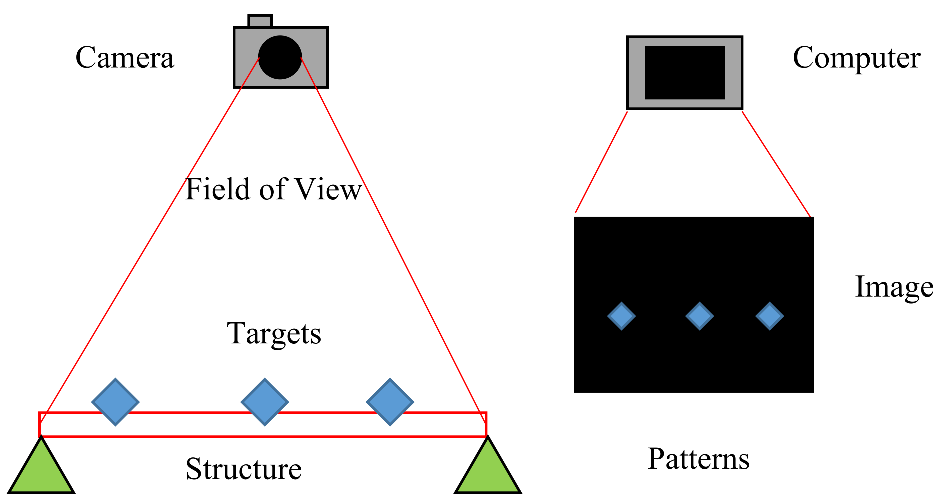


Figure 6 Schematic of computer vision SHM(196)

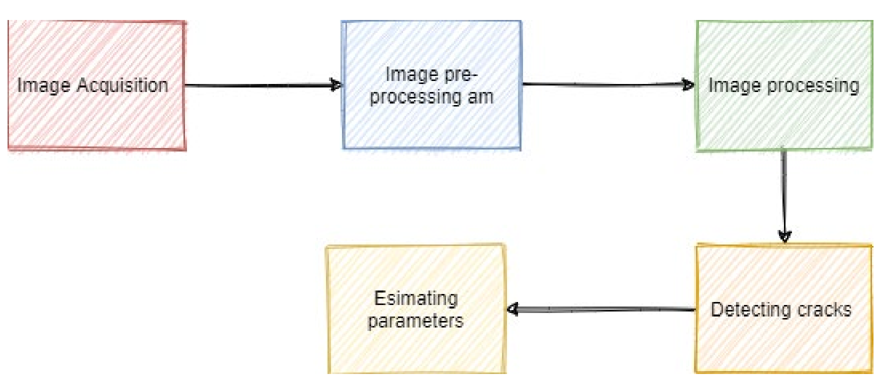


Figure 7 Image processing based architecture (204)

5.6 Data-driven based machine learning

As mentioned, signal-based (or data-driven) methods utilize the information obtained from monitored structures in order to reveal features reflecting the state of a system without any knowledge of the physical properties of the structure. These approaches are practical when (216):

- Sufficient numbers of sensors are available.
- Computational operations are costly in the SHM project
- Physical properties of the structure are unknown or complicated to be modeled.

It should be noted that methods based on extraction of features can identify damages independently via using different damages indices directly (54, 217-219) or by combining them with machine learning techniques for the purpose of pattern recognition (55). Herein, machine learning methods are applied to the features extracted from measured data to classify and predict the structural patterns obtained from sensors. Supervised, semi-supervised, and unsupervised are the categories for the different learning schemes in this scope. Three major issues are considered in the scope of machine learning, namely classification, regressions, and density estimation (60).

Kim and Philen (220) developed a machine learning algorithm called Adaboost that had the potential to identify corrosion and cracks on metals. Four signal processing techniques were examined, and the spectrogram based on short-time Fourier transform was chosen as the reliable damage diagnosis approach. They used the FE model of damages as training samples and examined the performance of the Adaboost on experimental specimens.

Three sets of experimental steel pipelines were investigated through 365 features extracted from ultrasonic signals in a study carried out by Ying et al. (221). Two feature selection methods using adaptive boosting algorithms automatically recognized suitable features for damage identification. Five classifications, namely adaptive boosting, modified adaptive boosting, SVM, and two methods combining adaptive boosting and SVMs, showed good performance for determining different damage scenarios.

A supervised method based on redundant information of the structure was introduced by Smarsly et al. (216). The algorithm used the inherent correlations among the amplitudes at peaks of the frequency spectra of accelerations from different sensors and deployed an ANN to map the relationship between the modal peak amplitudes of correlated sensors.

In a study done by Gui et al. (222), three optimization-based machine learning methods, including grid-search, partial swarm optimization, and the genetic algorithm were used for optimizing the penalty coefficient and kernel function parameter for the SVMs. Two damage features detected the damage scenarios of a scaled metal building model. They concluded that the genetic algorithm had better performance compared to the other optimization techniques. In a more recent study, Yu et al. (223) employed five different machine learning techniques, namely SVM, ANN, adaptive neuro-fuzzy inference system, regression tree model called M5P, and genetic expression programming to quantify Alkali-Silica Reaction (ASR)-induced elastic modulus degradation of unrestrained concrete. The study shows the proposed methods outperform three commonly-used empirical models in a wide range of statistical indices.

Gharehbaghi et al. (55) applied the AR time-series on acceleration signals for extracting sensitive features. In addition, an SVM algorithm was used in order to classify the different conditions of two specimens under environmental variations. The authors extracted features through statistical indices that were applied on coefficients and residuals of AR models then deployed a novel algorithm to find the sensitive features relating to deterioration and damage.

6 Popular SHM Benchmarks:

In a broad sense, a laboratory benchmark model provides an experimental study platform to validate the proposed methodology for anomaly detection (224). For expository reasons, SHM benchmark structures are divided into four regions of Europe, North America, East Asia, and Australia in this paper.

The majority of research projects in the USA, in this regard, have been supported by National Science Foundation (NSF), the Federal Highway Administration (FHWA), or other universities and laboratories such as LANL (Los Alamos National Laboratory), National Aeronautics, and Space Administration (NASA), United States Air Force (USAF), California Department of Transportation (CALTRANS), and Pacific Earthquake Engineering Research Center (PEER) among others.

In Europe, some collaborative projects on SHM have been organized. For instance, by the Ministry of Scientific Research and Technology (MURST) in Italy, and the Department of Trade and Industry (DTI) and Engineering and Physical Sciences Research Council (EPSRC), in the UK (225). Two primary schemes for cooperative research are the EC Framework Program projects and the EUREKA projects.

The Australian Network of Structural Health Monitoring (ANSHM) executes SHM projects in Australia on three projects: ARC Discovery, ARC Linkage, and CRC/CSIRO Projects. In the following sub-section, some of the important benchmark studies conducted around the world are summarized. A comprehensive review of SHM benchmarks is provided in (226).

6.1.1 P-block building

The P-block building is located at the Queensland University of Technology (QUT). It has been recently constructed at the Gardens Point campus of QUT, Australia, costing around AU$230M. The P-block has been awarded a 5-star Green Star rating from the Green Building Council of Australia (14). This concrete structure has ten floors equipped with accelerometers across four of its six above-ground stories (227). The most important part is that this benchmark utilizes an integrated vibration-sensing concept that has a software-based synchronization method, and it appears to be a promising choice for deployment in vibration monitoring of civil engineering structures.

On the first instrumented floor of this structure (i.e., level 4), six analog tri-axial sensors coupled with two single-axis accelerometers have been installed to record the vibration signals. As depicted in Figure 8, the sensors are positioned on the upper part of the structure (i.e., at levels 4, 6, 8, and 10) that appear to be more sensitive to the ambient vibrations originating from occupants' activities or environmental loads, such as wind load (228). Known as the testbed of Australia's first-ever long-term full-scale SHM system, P block building has interestingly hosted the 8th International Conference on Structural Health Monitoring of Intelligent Infrastructures (SHMII-8) on the first time this prestigious conference in the SHM field was organised in Oceania (229). More details regarding the P-block are presented in (230, 231)

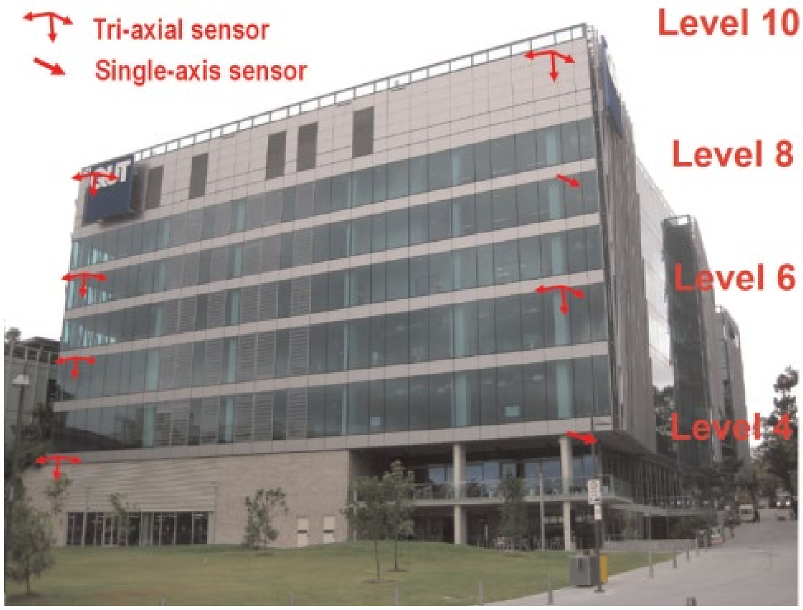


Figure 8 P-block building(227)

6.1.2 ASCE SHM Benchmark

Ventura (232) introduced this 4-story laboratory model at the 15th International Modal Analysis Conference. This structure is placed in the Earthquake Engineering Research Laboratory at the University of British Columbia (UBC) and is 2.5 meters wide and 3.6 meters high. Each level of this structure has two diagonal braces on each exterior face, as shown in Figure 9. The mass of each story is simulated with steel plates of various weights. Some of the braces can be removed to model different damage scenarios, and the connections between columns and beams can be loosened (224).

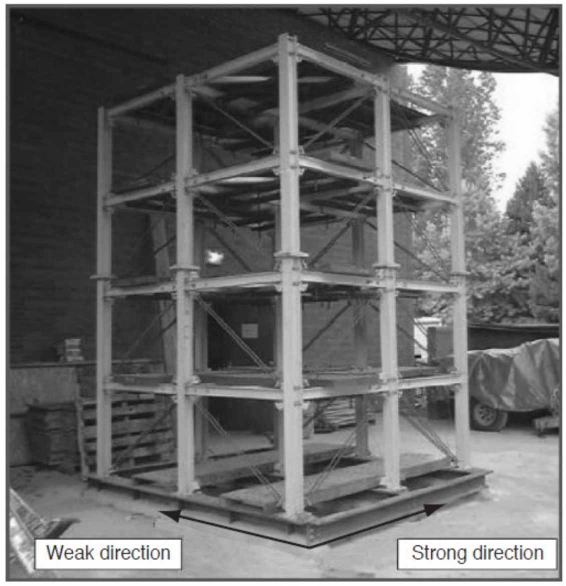


Figure 9 ASCE SHM Benchmark (224)

6.1.3 Bookshelf Frame Structure

The Los Alamos National Laboratory (LANL) has provided some experimental data sets, such as datasets, for bridges and buildings in the public domain (233). A bookshelf is one of the most popular datasets that is used as a damage detection testbed. This model is a three-story bookshelf with bolted joints and is constructed of metal columns and aluminum floor plates, as depicted in Figure 10 (233) (234). Moreover, four isolators allow the structure to sway in horizontal directions with the aid of a hydraulic shaker. Piezoelectric single-axis accelerometers equip the structure. Different damage simulations can be conducted by replacing the masses and changing the stiffness of the columns.

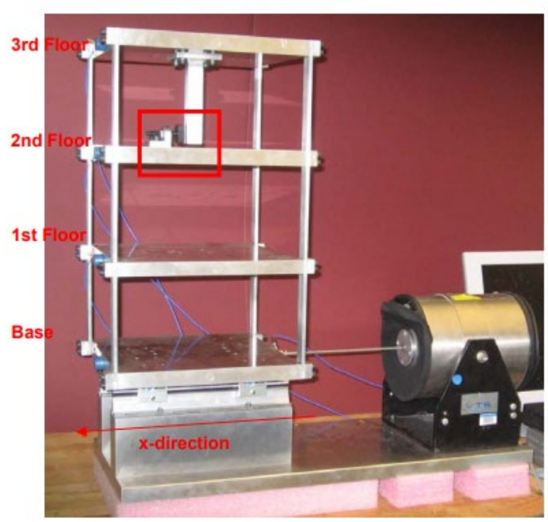


Figure 10 Bookshelf Frame Structure (233)

6.1.4 18-Story Steel Moment Frame

A one-third scale model of an 18-story steel high-rise and a protective frame was built and installed on the E-Defense shake table (Figure 11) (235). The model shows the behavior of a typical steel high-rise and responds to the earthquake as a steel moment-resisting frame. The model is similar to steel high-rise buildings constructed in the 1980s to 90s, where the column-to-beam strength ratio of 1.5 is provided to simulate a weak-beam strong-column mechanism. The building can be excited in one direction solely. The input ground excitation is a simulated ground vibration with long-period properties for a Tokai-Tonankai-Nankai subduction-zone earthquake.

Moreover, different types of sensors have been installed, and 879 data channels are recorded. Acquired signals of all channels can be obtained for all loading cases, composed of primary earthquake loadings and white-noise vibration. Notably, images from digital cameras record the overall model's condition vividly and the fracture at the beam ends.

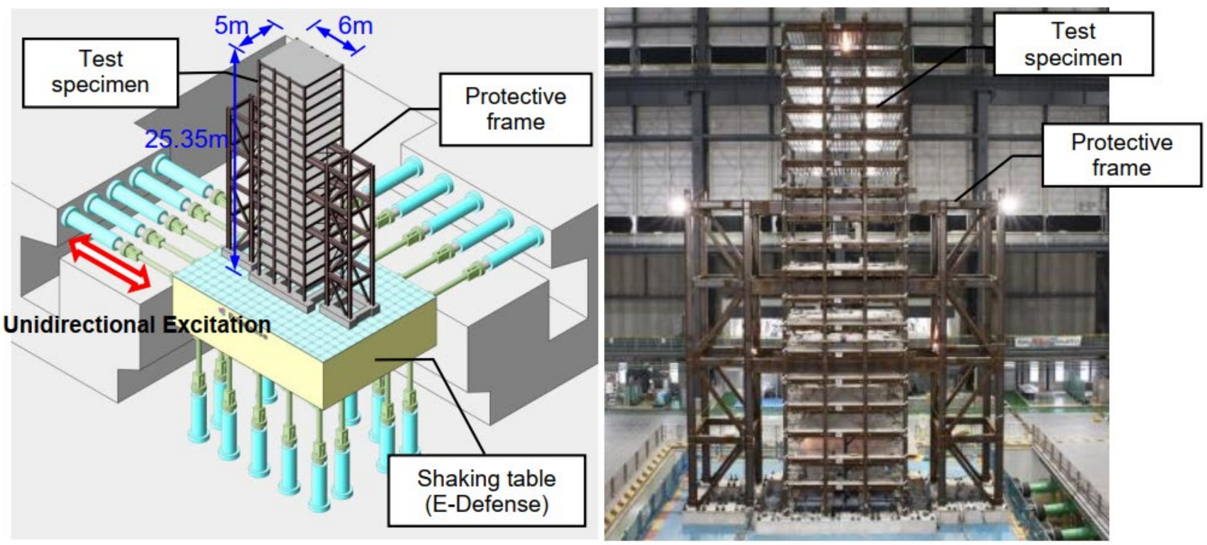
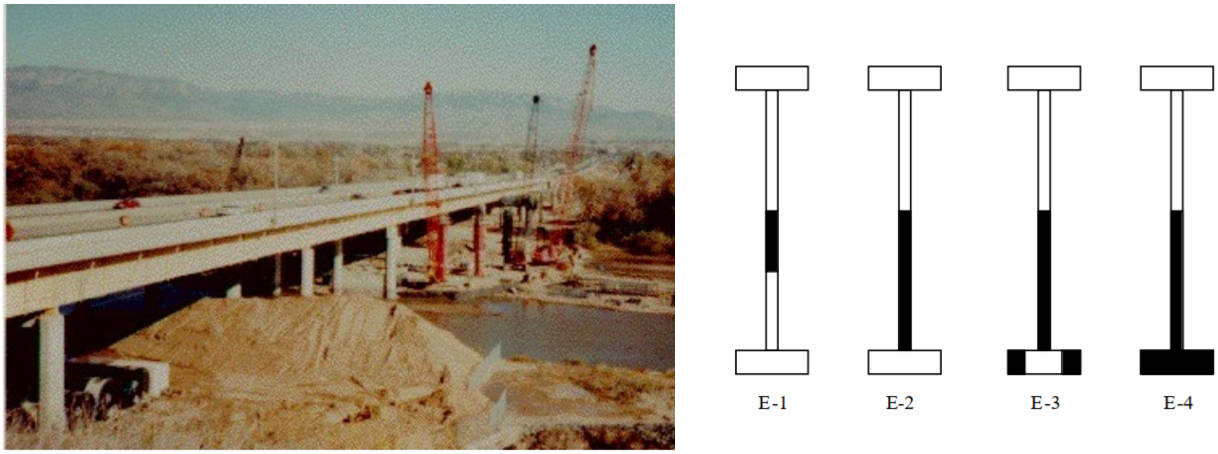


Figure 11 18-Story Steel Moment Frame(235)

6.1.5 I-40 bridge

This bridge was constructed over a highway in the Rio Grande River in Albuquerque, New Mexico (see Figure 12 a). The concrete deck was about 13.3 m wide and 18 cm thick, supported by two steel plate girders with a 3.05 m height (224). A number of modal tests were conducted after it had been closed in 1993. To this end, 13 accelerometers were installed to each of the two plate girders of the three spans and recorded 26 response measurements. The bridge was excited via a hydraulic actuator placed on the deck of the middle span closest to the abutment. Four levels of damages were introduced so as to simulate fatigue cracking by cutting the web and flange of the girder, as shown in Figure 12 b. More elaborated information on the modal experimental of this bridge is explained in (236).

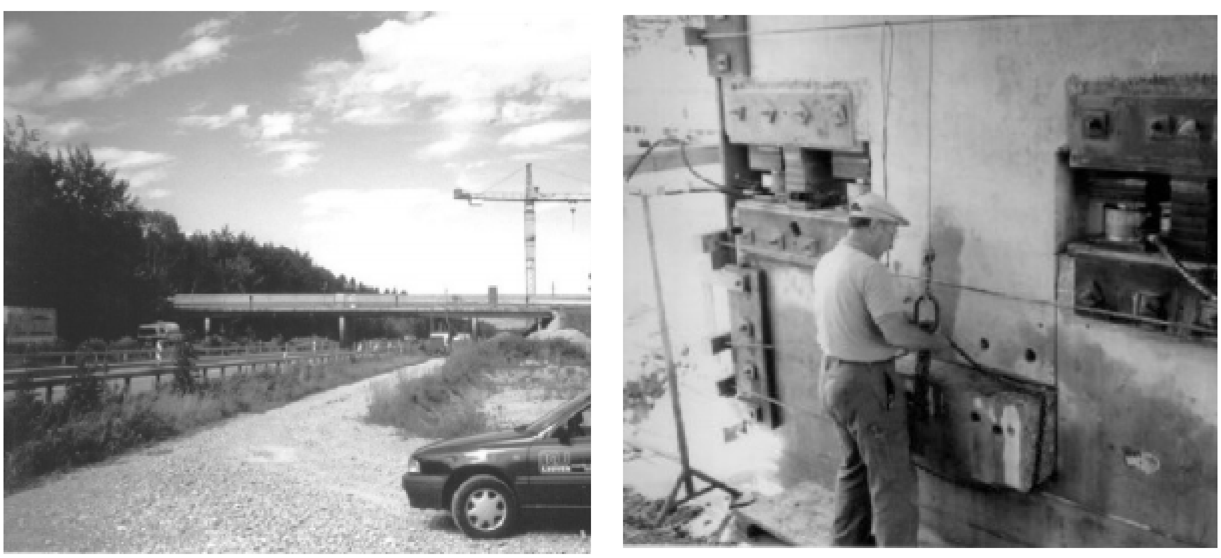


a) Picture of the bridge b) damage scenarios

Figure 12 I-40 Bridge in New Mexico. (224)

6.1.6 Z24 bridge:

This bridge was located in Canton Bern, Switzerland, as shown in Figure 13. It was a prestressed two-span bridged with two lanes and approximately 60m in length (237). In 1998, different progressive damages scenarios were implemented on this bridge, including settlement of piers, spalling f concrete, cutting of concrete hinges, landslide, ruptures of tendons, and failure of anchor bolts. However, the settlement was the central scenario that significantly impacted on the degradation of bending stiffness. The settlement was simulated by cutting the Koppigen pier and removing 0.4m of concrete to use six hydraulic jacks. Full details regarding this benchmark are illustrated in (238)



a) Overall view of the bridge b) Pier settlement using hydraulic jacks

Figure 13 Z24 bridge benchmark (237)

6.1.7 Tamar bridge:

The bridge is situated in the United Kingdom and used to be one of the longest suspended structures in England (239) (Figure 14). Firstly, in 1961 the structure had a 335 m span and a side span of 114 m. The anchorage and approach together amount to the total length of 643 m. Two concrete towers with a height of 73 m support the bridge. After a significant upgrade in the 1990s, several sensors were installed to assess the bridge's performance. These sensors recorded the data regarding cable tensions, wind velocity, temperature, and deflections. After years, in 2006, the engineers from the University of Sheffield installed an additional set of sensors consisting of eight accelerometers on orthogonal pairs to four cables and three sensors on the deck to extract vibrational data. The data had a 64 Hz sampling frequency at 10 minutes intervals. More details about this benchmark are provided in (240).

Figure 14 The Tamar suspended bridge

7 Conclusions

This paper has presented a review of the most promising and significant work reported in the literature regarding SHM and related methodologies developed over the past three decades. Additionally, a comprehensive categorization for anomaly detection was presented, and related studies in each subset were summarized and discussed. Moreover, the most widely studied SHM benchmarks were introduced at the end. The key findings of the literature review regarding the advantages and disadvantages of each anomaly detection method, as discussed in this paper, are summarized below:

Method	Pros.	Cons.
Displacement	• Detecting damage up to level 3 • Requiring a few sensors	• Insensitive to minor damage • Difficult to measure bridge structures over water using traditional displacement transducers.
Strain	• Detecting damage at levels 1 and 2	• Requiring large numbers of sensors

	• Capable of detecting damage in the presence of noise	• Strains are not reliable for long periods
Natural Frequencies	• Easy implementation • Relatively low cost • Require a limited number of sensors	• Sensitive to noise and vicinity of sensor or actuator • Usually limited to level 1 • Detect severe and single damage only
Mode-Shape	• More sensitive to damage than the natural frequency • More effective in noisy environments than frequencies	• Requiring large numbers of sensors • Having errors in locating damages in some areas • Insensitive to minor damage such as concrete cracks
Modal Curvature	• Able to detect slight damages	• Requiring many sensors • Existing errors in central difference approximation
MSE	• Requiring first few models • Addresses the levels 2 and 3 damage detection • Detecting multiple damages • Effective in noisy environments	• Accuracy decreases as the mode shape complexity increases
Damping	• Relatively low cost	• Having large standard deviations • Can be affected by operational effects • Damping levels may rise or fall depending on the damage
FRF	• Easy implementation • Relatively low cost • Multi damage case detection • Efficient in the existence of noise	• Mainly limited to level 2 • Sensitivity to numbers of modes • Sensitivity to frequency ranges
Matrix-based	• Addresses the levels 2 and 3 • Requiring few modes • Sensitive to faults through incomplete modal measurements • Sensitive to local defects	• Not sensitive to slight damages • Requiring well-distributed sensors • Requiring mass normalized mode shapes • Affecting the performance by using incomplete modal measurements

		• The precision relies on the mode shape data • Requiring higher-order modes for precise damage detection
Reliability	• Can be applied to complex structures	• The sensitivity of the results depend on the accuracy of the input data
AE	• Practical for complex damage mechanisms like composite materials • Can be deployed for real-time damage detection • Effective for global monitoring • Sensitive to slight damages	• Expensive • Requires skillful operator
Time-domain	• Detecting damage at levels 1 and 2 • Capable of detecting damage in the presence of noise • Sensitive to local damage • Not require a solving system of equations in finite element method • Capable of solving complex systems hard to model operating on partial models with a limited number of measurable excitation and/or response signals • Identifying dynamic characteristics of a system under ambient vibration • Inherent accounting for uncertainty through statistical tools	• Limit information about the location and severity of damage in the presence of noise • False-positive/negative results
Time-Frequency domain	• Effective in noisy environments • Addresses the levels 2 and 3	• Computationally expensive
Computer Vision	• Easy implementation • Low cost • Addresses the levels 2 and 3 • Ability to be automated	• Computationally expensive • Images quality degrades by environmental conditions

Data-Driven based Machine learning	• Ability to be automated • Addresses the levels 2 and 3	• Computationally expensive

Compliance with Ethical Standards

Conflict of Interest: On behalf of all authors, the corresponding author states that there is no conflict of interest.

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