Review on the Evolution of Civil Structure Health Monitoring Technology from Physical Detection to Data Intelligence

Yijie Wang
SWJTU-Leeds Joint School, Southwest Jiaotong University, Chengdu, 611756, China
cn23yw2@leeds.ac.uk

ABSTRACT

Civil engineering structures face various service risks, and the drawbacks of traditional manual testing are becoming increasingly prominent, driving the evolution of structural health monitoring from physical testing to data intelligence. This article systematically reviews the development of structural health monitoring technology, elucidates its core connotations and the evolution of damage identification tasks, and elaborates on the technical principles and applications of traditional non-destructive testing techniques in structural damage detection. It focuses on the application of machine learning in structural health monitoring, as well as technological breakthroughs in pixel level damage localization, fatigue crack dynamic capture, 3D damage assessment, and unlabeled dynamic response measurement using computer vision, and their engineering practices. Finally, the key challenges of current structural health monitoring technology were summarized, including poor algorithm robustness in extreme environments, insufficient cross scenario generalization ability, and lack of full lifecycle life prediction capability. This article provides a reference for the intelligent operation and maintenance of civil structures.

Keywords: Structure Health Monitoring, Nondestructive Testing, Machine Learning, Computer Vision.

1. INTRODUCTION

As the skeleton of modern civilization, civil engineering structures are inevitably threatened by environmental erosion, material aging, fatigue load, earthquakes, hurricanes and other extreme events during their long service life [1]. Structural degradation often begins with microscopic damage or physical property deviation that is difficult to detect by the naked eye. Without timely warning and intervention, these subtle changes may eventually evolve into catastrophic structural failure, causing huge loss of life and property." As shown in Figure 1, a series of catastrophic structural collapses worldwide highlight the fatal consequences of lacking effective structural health monitoring. The 2013 Rana Plaza collapse in Bangladesh, caused by illegal construction, overloading and substandard materials, killed over 1,100 people without real-time stress monitoring. The 2018 Morandi Bridge collapse in Italy, triggered by corroded prestressed cables and poor maintenance, claimed 43 lives with no continuous degradation tracking. The 2021 Champlain Towers South collapse in the U.S., driven by structural corrosion and ground subsidence, killed 98 people without systematic damage monitoring. The 2025 Dominican Jet Set nightclub collapse, caused by overload and post-fire damage, resulted in heavy casualties without load and deformation monitoring. These tragedies underscore the urgency of shifting from post-event repair to pre-event active monitoring in civil engineering.

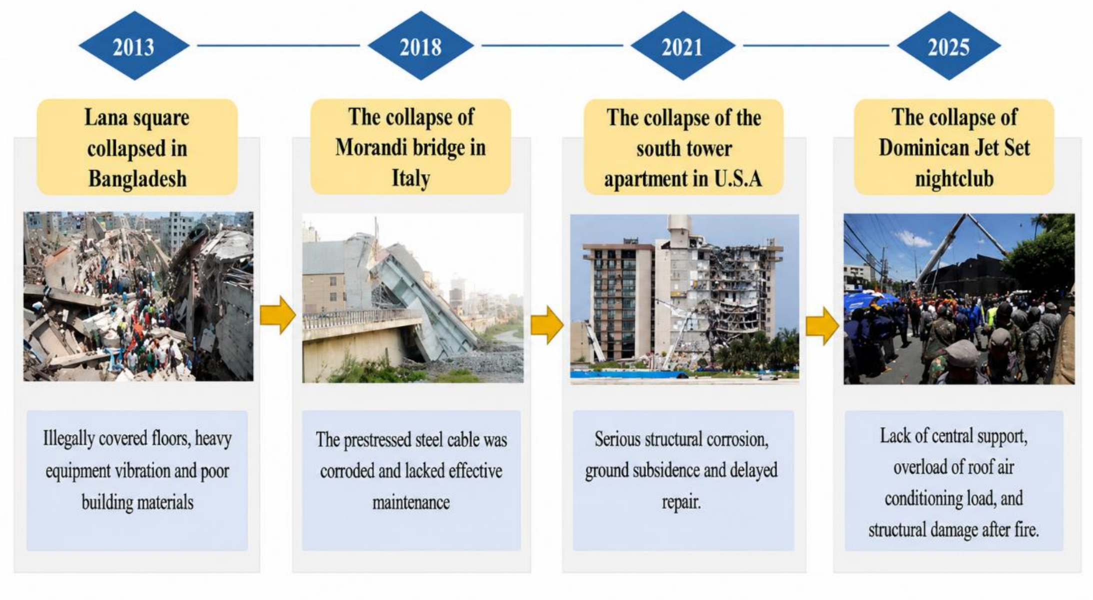

Figure 1. Accidents due to lack of structural health monitoring.

These accidents not only reveal the risk of brittle failure caused by corrosion, overload or design defects in the long-term service of the structure, but also highlight the urgency of the transformation from “passive repair after the event” to “active monitoring in advance”. According to statistics, although the establishment of a perfect monitoring system has early investment, the social costs and reconstruction costs it avoids far exceed the monitoring costs. This demand for diagnosis and treatment integration has become the core driving force of the contemporary civil engineering discipline.

2. DEFINITION AND CONNOTATION OF STRUCTURAL HEALTH MONITORING (SHM)

The traditional structure security mainly depends on the experience based artificial vision inspection. However, this mode has strong subjectivity, low inspection frequency and difficult to reach the internal or hidden parts of the structure, and its limitations in large sea crossing bridges, super high-rise buildings and complex spatial structures are increasingly prominent [2]. In order to overcome these shortcomings, structural health monitoring (SHM) technology came into being.

SHM is defined as the use of on-site sensing technology to obtain the environment, load and response parameters of the structure. Through real-time or regular analysis and processing, it aims to track the state of the structure, evaluate operation changes and identify early damage signs [3]. A typical and complete SHM system is a highly integrated technology chain, covering the bottom perception layer (sensing), the middle transmission and processing layer (signal processing) and the top decision-making layer (Health Assessment) [1]. To address these limitations, structural health monitoring (SHM) technology emerged, as illustrated in Figure 2, which systematically outlines the three-tier architecture of a typical SHM system.

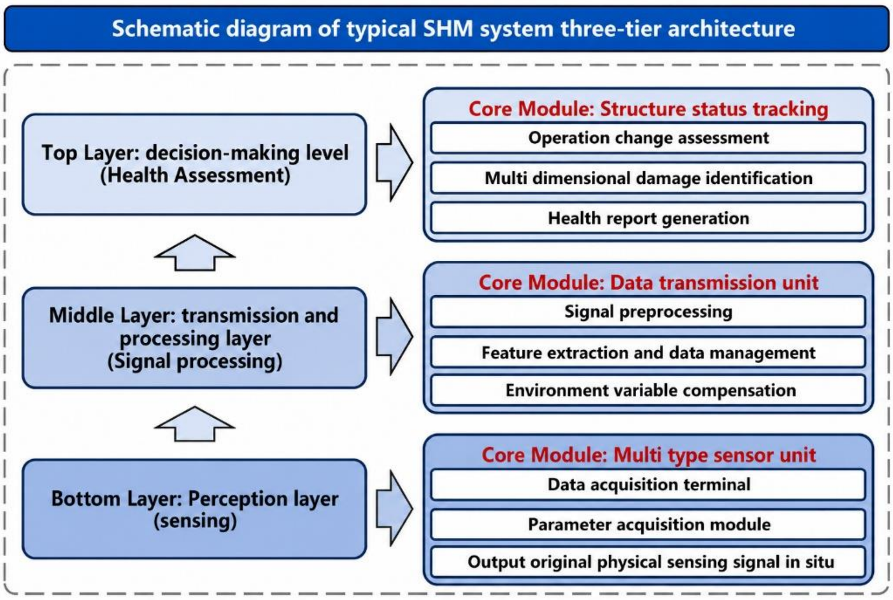

Figure 2. The three-tier architecture of a typical structural health monitoring (SHM) system.

2.1 From damage identification to intelligent perception: evolution of task level

The core task of SHM is to conduct multi-dimensional quantitative assessment of structural damage. According to the classical classification framework proposed by rytter, damage identification is divided into four progressive energy levels [4]. This framework has become the core guidance for the development of the whole SHM field:

Level 1 (existence): determine whether the structure has been damaged, which is the most basic task of SHM, and answer the core question of “is there a problem with the structure”;

Level 2 (location): determine the spatial location of the damage in the structure. After confirming the existence of the damage, further locate the specific location of the damage to provide guidance for maintenance;

Level 3 (degree): quantify the severity of damage and evaluate the impact of damage on the current performance of the structure;

Level 4 (prediction): assess the impact of damage on structural safety and predict its remaining service life (rul), providing support for long-term operation and maintenance decisions.

With the rapid development of intelligent materials and embedded systems, the vision of modern SHM has gone beyond the simple “state monitoring” and is evolving towards the intelligent control ability of giving structures “perception and adaptation to environmental changes” [5]. This evolution makes the structure tend to be biological in function. Through the built-in “nervous system”, it can carry out self-diagnosis and even assist self-repair, and finally realize the self-operation and maintenance of the structure in the whole life cycle.

2.2 Building closed-loop systems and verifying design assumptions

The essence of SHM is to build a closed-loop system throughout the whole life cycle of the structure [6]. Starting from the original physical signal obtained by the sensor, the noise interference is removed by feature extraction, and finally the health assessment report is given by the decision-making system based on data-driven or physical model. This process is not only for disaster prevention and mitigation, but also has deep scientific value.

As Zhang (2001) emphasized [7], the real-time observation data provided by SHM is the continuous verification of initial design assumptions (such as boundary conditions, load modes and material constitutive models). In the traditional civil engineering design, engineers often need to make a lot of simplified assumptions about loads, material parameters and boundary conditions. The cognitive uncertainty brought by these assumptions will lead to the deviation between the design results and the real performance of the structure. The long-term monitoring data provided by SHM can enable engineers to compare the real performance and design expectations, so as to modify the theoretical model and eliminate the cognitive uncertainty in the design stage. This feedback cycle from data to knowledge marks that civil engineering has moved from traditional empirical design to a new era of intelligent operation and maintenance based on real performance.

3. HIGH FREQUENCY DETECTION TECHNOLOGY OF LOCAL MICRO DAMAGE

3.1 Piezoelectric impedance method (EMI)

The essence of SHM is to build a closed-loop system throughout the whole life cycle of the structure [6]. Starting from the original physical signal obtained by the sensor, the noise interference is removed by feature extraction, and finally the health assessment report is given by the decision-making system based on data-driven or physical model. This process is not only for disaster prevention and mitigation, but also has deep scientific value.

Electrical impedance (EMI) is one of the most representative technologies in the field of high frequency local monitoring. Its core logic is based on the “electromechanical mutual inductance” characteristics of piezoelectric ceramics (PZT). Liang, sun and Rogers (1994) first proposed an electromechanical coupling model to describe this phenomenon, which laid the theoretical foundation of EMI [8]. The coupling admittance formula is as follows:

$$Y(\omega) = i\omega \frac{w_A l_A}{h_A}\left(\bar{\epsilon}_{33}^{T} - \frac{Z}{Z_A + Z} d_{32}^{2} \bar{Y}_{22}^{E}\right) \tag{1}$$

From the perspective of physical mechanism, PZT chip has the dual functions of actuator and sensor: when PZT chip is driven by high-frequency alternating voltage, it will produce high-frequency mechanical vibration and transmit this vibration to the host structure; At the same time, the mechanical impedance of the host structure will reverse act on the PZT chip, changing the electrical response of PZT, which will eventually be reflected in its electrical admittance signal. Liang et al. (1994) showed that [8], there is a direct mapping relationship between the complex admittance of PZT and the mechanical impedance of the structure: any slight change in local stiffness, mass or damping (i.e. damage) will lead to the deviation or peak distortion of the admittance spectrum. By monitoring this change, accurate detection of local damage can be achieved. The dual-function mechanism of PZT chips and the corresponding admittance spectrum changes, as illustrated in Figure 3, provide a clear physical explanation for how EMI technology achieves accurate local damage detection.

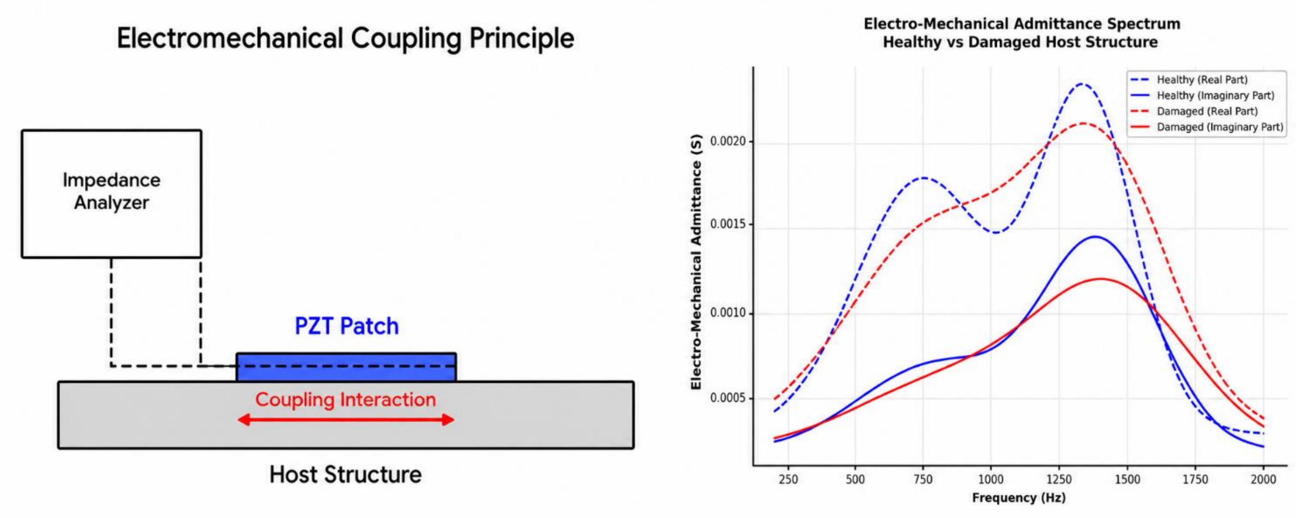

Figure 3. The electromechanical coupling principle and admittance spectrum for PZT-based EMI damage detection.

3.2 Ultrasonic attenuation technology

Unlike EMI, which is based on “point” impedance monitoring, ultrasonic detection technology based on wave propagation theory provides another local characterization dimension, which can cover a wider range and realize the quantitative evaluation of distributed micro damage. The ultrasonic longitudinal wave (L-Wave) transmission method proposed by Shah et al. (2000) shifted the perspective from “time delay” to energy loss [9]. When the ultrasonic wave propagates in the medium containing microcracks, the beam will have complex scattering and energy attenuation. When there is a micro crack in the medium, the wave front of the ultrasonic wave will reflect, refract and scatter at the crack interface, and the original directional sound energy cannot be captured by the receiving sensor. With the increase of damage degree, there is a significant correlation between the change of effective wave path and energy dissipation, which makes the SHM system transition from simple “damage detection” to a new stage of “damage degree quantification”.

4. TRADITIONAL NONDESTRUCTIVE TESTING (NDT) TECHNOLOGY SYSTEM

4.1 Acoustics and ultrasonic methods

Acoustic and ultrasonic technology has a long history in the integrity evaluation of concrete and masonry structures, and its core logic is the reflection and scattering of waves at different media interfaces and damage sites. McCann and Forde (2001) discussed in depth the application of sonic transmission [10], which uses 500 Hz to 10 kHz compression wave to penetrate structural members. By accurately analyzing the variation of wave velocity, engineers can effectively evaluate the consistency of materials and identify internal cavities, which is the core technology path of early acoustic NDT.

4.2 Vibration based NDT

Different from the local NDT method focusing on points or surfaces, the vibration based method indirectly identifies damage by monitoring the overall dynamic characteristics of the structure. The theoretical system is based on a core assumption: structural damage (such as local stiffness reduction) will inevitably lead to observable deviation of its overall dynamic parameters (such as frequency, mode shape or damping) [11,2].

4.3 Precision transition of laser interference and nondestructive evaluation

In order to overcome the limitations of traditional contact sensors in spatial resolution, the 1990s witnessed the introduction of optical precision measurement technology. Nokes and cloud (1993) used laser Doppler vibrometer (LDV) and electronic speckle pattern interferometry (ESPI) to capture extremely fine local mode shapes in the high frequency band of 10 kHz [12]. As shown in Table. 1, the multi-physical field adaptability of traditional non-destructive testing (NDT) technologies in structural health monitoring is systematically summarized, covering applicable damage scales, inspection ranges, environmental adaptability, typical application scenarios and corresponding references.

Table 1. Multi physical field adaptability of traditional NDT technology in structural health monitoring.

Physical Field	Applicable Damage Scale	Inspection Range	Environmental Adaptability	Typical Application Scenarios	References
Acoustic/Mechanical wave	Surface to internal; planar flaws ≥0.1 mm, volumetric flaws ≥1 mm	Metals: 0–10 m (frequency-dependent); Non-metals: 0–5 m	Requires couplant; usable 10–60 °C; immune to EMI; rough surfaces degrade performance; not suitable for porous materials	Thick-wall structures, welds, delaminations, cracks, thickness gauging; metallic/composite pressure vessels	[40], [43]
Electromagnetic radiation	Volumetric flaws ≥0.2 mm (energy-dependent); planar flaws ≥1 mm (normal to beam)	X-ray: 0–50 mm (steel); γ-ray: 0–300 mm (steel)	Radiation hazard requiring shielding; usable −20–80 °C; sensitive to density contrast; limited by high-density materials	Castings, welds, volumetric defects (porosity, inclusions); aero-engine components	[43], [46]

Table 1. (continued) Multi physical field adaptability of traditional NDT technology in structural health monitoring.

Physical Field	Applicable Damage Scale	Inspection Range	Environmental Adaptability	Typical Application Scenarios	References
Magnetic field	Surface-breaking flaws ≥30 µm (wet); ≥100 µm (dry); near-surface ≤3–5 mm	Surface and near-surface; limited per-scan area	Ferromagnetic materials only; usable 5–50 °C; oil/coating interferes; requires demagnetization; sensitive to electromagnetic interference	Steel structures, weld surface cracks, SCC; automotive parts, bearings	[43], [49]
Electromagnetic field	Surface/near-surface; cracks ≥50 µm, wall loss ≥1%; depth ≤5 mm (skin effect)	Surface/near-surface; single probe ≤50 mm; pipelines up to 100 m (remote-field ECT)	Conductive materials only; usable −20–80 °C; coatings interfere; sensitive to EMI; high-temperature probes available	Surface/near-surface cracks and corrosion in conductors; turbine blades, rails, tubes	[41], [45]
Capillary action /Liquid penetration	Surface-breaking flaws ≥0.1 µm (fluorescent); ≥25 µm (visible dye)	Surface-only; large-area coverage up to 10 m²/h	Non-porous materials only; usable 10–50 °C; surface roughness affects results; chemical sensitivity; not for high temperatures	Surface cracks in all non-porous materials; welds, castings, forgings; aerospace structures	[43], [49]
Acoustic/ Elastic wave	Dynamic defects (crack growth, plasticity); micro- to macroscale ≥1 µm	Global structural monitoring; localization accuracy sensor-dependent	Compatible with most materials; usable −20–80 °C (special sensors up to 1000 °C); noise-sensitive; requires coupling; suitable for high pressure/vacuum	Real-time monitoring; pressure vessels, bridges, tunnels, composites; crack propagation monitoring	[46], [47]
Thermal field / Infrared radiation	Surface/near-surface; flaws ≥1 mm, depth ≤5 mm (active heating)	Surface-only; large-area scanning up to 100 m²/h	Non-contact; usable −40–2000 °C (camera-dependent); affected by ambient temperature; emissivity-dependent; immune to EMI	Rapid large-area screening; composite delaminations, concrete voids, electrical overheating	[42], [48]
Acoustic/ Mechanical guided wave	Wall loss ≥1%, cracks ≥1 mm; plates/pipes	Long-range: pipelines 10–100 m per direction; plates 5–50 m per direction	Requires couplant; usable 0–80 °C; disturbed by geometry, attachments, and corrosion; immune to EMI	Long-distance pipeline/tank corrosion monitoring; bridge cables, steel structures; hard-to-reach areas	[48], [49]

5. MACHINE LEARNING ENABLED STRUCTURAL HEALTH MONITORING：ADVANCED MACHINE LEARNING PARADIGM AND LOGICAL EVOLUTION IN STRUCTURAL HEALTH MONITORING

Although the traditional physical modeling methods have good interpretability, they gradually show significant limitations in practical engineering applications. In real engineering scenarios, the lack of damage marker data, the interference of environmental noise and the data integrity caused by the limited energy of sensors constitute the core pain points in the field of structural health monitoring, which makes the traditional methods often unable to deal with multi-source heterogeneous data in complex real environment.

Bao and Li [13] further clarified the necessity of this change, and pointed out that the traditional method is difficult to deal with the “high degree of incompleteness” caused by the fact that the number of sensors in the actual structure is far less than the degree of freedom, and the coupling problem between environmental factors and damage effects on modal parameters-in the real environment, the impact of environmental factors such as temperature, humidity, load on structural modal parameters is often far greater than the changes caused by early minor damage, and it is difficult to effectively separate the two by the traditional method.

With the popularity of Internet of things (IOT) and big data technology, data-driven methods have become the mainstream development direction in this field. Machine learning realizes the transformation from “original data” to “state insight” by learning the feature mapping in monitoring data. Malekloo et al. [14] pointed out that this transformation made real-time and online damage diagnosis possible, which greatly made up for the lack of efficiency of traditional methods. As shown in Figure 4, the whole-life-cycle process of structural health monitoring (SHM) based on the SPR framework is systematically illustrated, covering operational evaluation, data acquisition, feature extraction, statistical modeling and decision support, which clearly demonstrates the application path of machine learning in SHM.

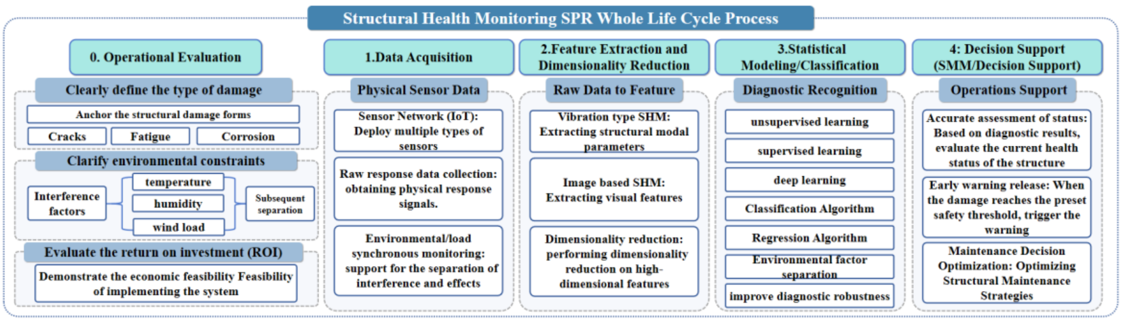

Figure 4. Structural Health Monitoring SPR Whole Life Cycle Process.

5.1 Unsupervised learning and probabilistic anomaly detection

In the actual engineering scenario, for the infrastructure in service, the structure is in normal working state most of the time in the whole life cycle, and the cost of obtaining damage samples is very high. In this context, unsupervised learning has become the core of identifying structural changes.

Santos et al. [15] systematically compared the algorithms based on kernel function (such as OC-SVM, SVDD and KPCA), and proved that the kernel method can effectively deal with the disturbance of variable working conditions and realize the effective identification of unknown damage by projecting the low dimensional nonlinear data into the high dimensional linear space.

Sarmadi and Yuen [16] used extreme value theory (EVT) to build decision scores, providing a statistical confidence threshold for anomaly detection. For example, at the 95% confidence level, anomalies exceeding this threshold can be determined as structural damage. This result has clear statistical interpretation and can directly support operation and maintenance decisions.

Gomez Cabrera and Escamilla Ambrosio [17] further proposed the idea of hierarchical classification. On the basis of anomaly detection, by integrating ANN, CNN, SVM and other algorithms, it realized the quantitative evaluation of the degree of damage, and promoted SHM from the qualitative detection of “whether there is damage” to the quantitative evaluation of “how serious the damage is”.

For the discrete and incomplete signals generated by self-powered sensor networks, Salehi et al. [18] proposed an integration framework integrating low rank matrix completion with support vector machine (SVM), k-nearest neighbor (k-NN) and artificial neural network (ANN).

5.2 Deep Learning and Automatic Learning of Temporal Features

Deep Learning (DL) techniques, represented by Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), have achieved automatic feature extraction, greatly unleashing the potential of data. Ye, Jin, and Yun [19] pointed out in their review of deep learning that DL can directly process multi-source heterogeneous on-site monitoring data, effectively bridging the gap between SHM and structural maintenance management (SMM).

The feature extraction of time-series data is the core problem of vibration type SHM. Entezami et al. [20] proposed a feature extraction method based on iterative time series modeling, whose core logic is to use autoregressive (AR) models to capture linear or nonlinear components in dynamic responses, and characterize the physical degradation of structures through changes in model coefficients.

On this basis, deep learning models further enhance the ability to extract temporal features. For example, the MA-LSTM-AE model introduced by Ghazimoghadam and Hosseinzadeh [21] has a core “multi head self-attention mechanism” similar to human vision, which can automatically focus on the time domain segments most sensitive to damage in acceleration signals through mathematical weight allocation, achieving more accurate damage localization and recognition.

5.3 Application Practice in Typical Engineering Scenarios

Ye, Sun, and Lu [22] proposed a machine learning based warning method for predicting the vibration amplitude of main beams and tower columns in response to the safety issues of long-span cable-stayed bridges under extreme wind speed conditions such as typhoons. The stiffness of long-span cable-stayed bridges is relatively low, and they are prone to significant wind-induced vibrations under the strong winds of typhoons. This study utilizes probability density functions and cutting-edge ML algorithms to predict the future vibration amplitude of structures minutes in advance based on real-time monitoring data, in order to avoid the occurrence of disasters and accidents.

Wang et al. [23] reviewed innovative monitoring technologies for railway bridges, with a particular emphasis on the combination of fiber optic sensing, digital image correlation (DIC), and machine learning, providing a new technological path for high-precision monitoring of railway bridges. In addition, the “Model free” damage detection framework proposed by Neves [24] achieves rapid assessment of bridge status solely through statistical changes in monitoring data without relying on complex finite element analysis, greatly reducing the deployment cost of monitoring.

Aoki et al. [25] proposed a probabilistic connectivity assessment framework that considers spatial correlation. This method integrates the multiple disaster impacts of earthquakes and tsunamis, and uses vulnerability curves and the total probability theorem to evaluate the impact of bridge group damage on the functionality of the entire transportation network.

6. VISUAL BASED INTELLIGENT RECOGNITION AND HIGH-PRECISION QUANTIFICATION OF STRUCTURAL DAMAGE

6.1 Pixel level damage localization

Traditional image processing methods, such as edge detection, have poor robustness in complex backgrounds and lighting changes in outdoor environments, making it easy to mistake shadows and textures for cracks. Liu et al. [26] first introduced the U-Net fully convolutional network into concrete crack detection, which is a milestone in their research. This study addresses the core pain point of extreme imbalance between positive and negative samples in crack detection by introducing the Focal Loss function, demonstrating that U-Net outperforms traditional deep convolutional neural networks (DCNN) in complex backgrounds and lighting changes, achieving end-to-end pixel level crack localization.

Ataei et al. [27] compared the performance of YOLO-v7 instance segmentation and Mask R-CNN in concrete crack and peel detection. The research results indicate that YOLO-v7 has average inference speed (40 FPS) and average accuracy (mAP@0.5 =96.1%) is significantly better than Mask R-CNN, confirming its superiority in real-time monitoring scenarios

Regarding the specificity of steel structures, Kim et al. [28] proposed a detection architecture for Steel Frame Damage, which utilizes deep convolutional neural networks to capture the peeling and deformation of steel surfaces, solving the detection difficulties caused by surface reflection and complex texture of steel structures.

For masonry structures, Sangirardi et al. [29] extended their research focus to Masonry Structures and systematically explored the evolution of masonry cracks, providing a new technological path for monitoring ancient buildings and old masonry structures.

6.2 High precision quantification of crack width

Traditional pixel physical conversion often assumes that the camera is shooting vertically, but in actual field monitoring, the shooting angle is often tilted, and camera distortion can also cause errors. Yang et al. [30] proposed a new method based on F-CNN model combined with Pixel Nonlinear Calibration to address this issue. By compensating for camera distortion and shooting angle errors, a nonlinear mapping between pixel coordinates and physical coordinates was established, achieving sub-pixel level crack width measurement and greatly improving the reliability of automated inspection. This technology can maintain sub millimeter level measurement accuracy even in non-vertical shooting scenarios. Sangirardi et al. [29] further applied this logic to masonry structures, tracking the evolution of cracks between masonry in real-time, providing support for long-term degradation monitoring of old structures.

6.3 Dynamic capture and 3D damage assessment of fatigue cracks

For fatigue cracks in steel structures, static image detection is often difficult to identify: in the unloaded state, fatigue cracks are closed and almost indistinguishable to the naked eye, which leads to a very high false alarm rate in static detection. To address this pain point, Kong and Li [31] proposed a short video stream monitoring method based on consumer grade cameras. This method captures the surface motion of steel structures under reciprocating loads through Shi Tomasi feature detection and KLT feature tracking, and effectively identifies fatigue cracks using the local circular region motion difference algorithm.

Pan [32] proposed a 3D vision driven damage detection and loss estimation framework in his research. This technology not only identifies damage, but also evaluates the impact of damage on the overall performance of the structure through 3D point cloud reconstruction, providing a scientific basis for rapid post earthquake disaster damage assessment. As shown in Table. 2, the performance of damage detection algorithms for different material structures is systematically compared, covering recognition accuracy, 2D/3D quantification capability, representative algorithms and corresponding references for concrete, steel, masonry and ancient structures.

Table 2. Comparison Table of Performance of Damage Detection Algorithms for Different Material Structures.

Structure Type	Recognition Accuracy	Quantification Capability (2D/3D)	Representative Algorithms	Representative References
Concrete	U-Net: Pixel-level crack recognition, IoU=89.2% YOLO-v7: mAP@0.5=96.1%, inference speed=40 FPS F-CNN: Sub-pixel level crack width measurement, accuracy=±0.02 mm	2D as the main type, supporting pixel-to-physical quantity conversion of crack position and width; 3D point cloud can be combined to quantify the 3D morphology of surface damage	U-Net, F-CNN, YOLO-v7	[53], [54], [55]
Steel Structure	Shi-Tomasi + KLT: Fatigue crack detection accuracy rate=92.5%, miss detection rate < 3% DCNN: mAP@0.5=91.3% for steel structure spalling/deformation recognition 3D Point Cloud: Damage deformation quantification accuracy=±0.1 mm	2D: Dynamically capture the opening and closing characteristics of fatigue cracks to realize 2D quantification of crack position/length 3D: Realize 3D quantification of structural deformation and damage volume through point cloud reconstruction	Shi-Tomasi feature detection + KLT feature tracking, local circular area motion difference algorithm, DCNN, 3D Point Cloud	[56], [57], [58]

Table 2. (continued) Comparison Table of Performance of Damage Detection Algorithms for Different Material Structures.

Structure Type	Recognition Accuracy	Quantification Capability (2D/3D)	Representative Algorithms	Representative References
Masonry Structures	Pixel-level crack recognition, IoU=85.7%; real-time crack evolution tracking accuracy=±0.05 mm	2D: Realize full-cycle quantification of crack position, width and evolution process 3D: Scalable to quantify the overall deformation of masonry structures and the spatial distribution of cracks	Computer vision crack tracking algorithm, semantic segmentation algorithm	[59]
Ancient Structures	Multi-view geometry: Millimeter-level 3D deformation detection, accuracy=±0.5 mm CNN/Multispectral imaging: Pixel-level recognition of ancient building diseases, overall accuracy=93.28%, Kappa coefficient=0.91	2D: Realize pixel-level recognition and quantification of surface diseases (cracks, spalling, weathering) 3D: Realize 3D quantification of global settlement, tilting, deflection and other deformations	Multi-view geometry, 3D Point Cloud, CNN/Multispectral imaging algorithm	[60], [61]

7. DYNAMIC VISUAL RESPONSE MEASUREMENT

7.1 Target-free planar tracking and micro-vibration amplification

Early visual measurements often required the placement of artificial targets on the surface of structures. To address this pain point, Dong et al. [33] proposed the “Virtual Markers” framework, which utilizes the natural texture of the structural surface as tracking points to achieve multi-point synchronous recognition in the monitoring of grandstand structures. The core of this technology is to use feature operators such as SIFT or SURF to extract natural feature points on the surface of the structure.

In order to further enhance the ability to capture small vibrations, Zhu et al. [34] developed a robust recognition system that focuses on using phase information for motion estimation and amplification, effectively improving the recognizability of small vibration signals.

7.2 Target-free 3D dynamic response measurement

While the aforementioned target-free planar tracking methods enable efficient 2D dynamic response acquisition, they fail to capture the full spatial motion of structures. Early 3D visual measurements in this field mainly relied on binocular vision systems. Shao et al. [35] developed a target free 3D vibration measurement system based on binocular vision, which utilizes deep learning assisted feature point matching to successfully obtain the dynamic response of the structure in three spatial directions. Binocular vision can accurately calculate depth information through the disparity between two cameras, resulting in high measurement accuracy and strong robustness.

However, binocular vision requires two cameras, and the deployment and calibration costs are high. In order to further simplify the system, Shao et al. [36] further simplified the system and achieved 3D displacement estimation through a monocular camera. Although its robustness is slightly inferior to binocular in extreme working conditions, its deployment convenience is greatly improved. With only one ordinary consumer grade camera, 3D displacement measurement can be achieved, which is very suitable for large-scale promotion and application.

Khuc et al. [37] combined unmanned aerial vehicle (UAV) technology with computer vision, using UAVs equipped with cameras to closely observe high-altitude areas. At the same time, by combining motion compensation algorithms, they solved the measurement error caused by the UAV's own shaking and achieved displacement measurement of high-altitude areas, solving the monitoring problem of high-altitude or difficult to reach areas.

8. STRUCTURAL RECOGNITION AND DATA QUALITY ASSURANCE

8.1 Unit Impact Surface (UIS) and Damage Localization in Unrestricted Traffic

Traditional bridge damage detection often requires traffic closure and manual excitation, which can seriously affect the normal operation of traffic and result in high costs. In response to this issue, Khuc and Catbas [38] proposed a groundbreaking study that identified vehicle loads through CV (based on HOG + AdaBoost cascade classifier) and synchronously measured structural responses, constructing a displacement unit influence surface (UIS).

8.2 End to end modal parameter identification

Yang et al. [39] proposed the CNN-LSTM deep learning architecture. The logic lies in using CNN to extract spatial features of videos and LSTM to capture frequency evolution on time series, thus directly predicting the first three natural frequencies of the structure from the original pixel stream, opening up a new approach for real-time modal analysis. This model exhibits strong robustness, with a prediction mean absolute error (MAE) as low as 0.45-1.5 Hz, outperforming traditional finite element analysis methods in noisy and viewpoint changing scenarios.

8.3 Data anomaly detection: system quality control

Bao et al. [50] proposed a data anomaly detection method that integrates CV and deep learning. This technology can simulate the visual inspection process of experts, automatically identify and eliminate erroneous data points caused by system failures, wireless interference, or extreme environmental noise, ensuring the correctness of subsequent structural safety assessment conclusions.

Lydon et al. [51] further developed a composite system for bridge health monitoring, integrating CV collection and deep learning data processing. It can automatically classify load types and calculate structural stresses in large traffic flow environments, achieving full process automation from data collection to evaluation.

9. CHALLENGES AND FUTURE PROSPECTS

In summary, the application of SHM in civil engineering has made significant progress, from early physical methods to current deep learning and vision technologies that have the ability to replace traditional sensors in limited environments. But the field still faces some core challenges:

Robustness in Extreme Environments: Under extreme weather conditions such as fog, rain, and low light, the accuracy of visual monitoring will significantly decrease. How to improve the robustness of algorithms in these extreme environments is the core research direction for the future [52];

Cross scenario universal model: Current algorithms are often trained for specific scenarios, and their generalization ability across materials and structures is insufficient. Developing a universal damage detection model is the core demand of the industry;

Whole life cycle assessment: Current technology mainly focuses on condition monitoring, and how to predict the remaining life of structures based on visual data is an important direction for the future.

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