buildings

Review

The Current Development of Structural Health Monitoring for Bridges: A Review

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Abstract: The health monitoring system of a bridge is an important guarantee for the safe operation of the bridge and has always been a research hotspot in the field of civil engineering. This paper reviews the latest progressions in bridge health monitoring over the past five years. This paper is organized according to the various links of the bridge health monitoring system. Firstly, the literature on monitoring technology is divided into two categories, sensor technology and computer vision technology, for review. Secondly, based on the obtained monitoring data, the data processing methods including preprocessing, noise reduction, and reconstruction are summarized. Then, the technical literature on abnormal data early warning systems is summarized. The recent advances in vibration-based and non-destructive testing-based damage identification methods are reviewed in the next section. Finally, the advantages and disadvantages of the existing research and the future research directions are summarized. This review aims to provide a clear framework and some reliable methods for future research.

Keywords: structural health monitoring; sensing technology; data denoising; data reconstruction; early warning; finite element model updating; damage identification

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Citation: Deng, Z.; Huang, M.; Wan, N.; Zhang, J. The Current Development of Structural Health Monitoring for Bridges: A Review. *Buildings* **2023**, *13*, 1360. https://doi.org/10.3390/buildings13061360

Academic Editor: Gianfranco De Matteis

Received: 28 March 2023
Revised: 27 April 2023
Accepted: 16 May 2023
Published: 23 May 2023

1. Introduction

As the core pillar of economic development, the bridge transportation system has been highly valued by countries around the world in recent decades. With the rise of bridge engineering, bridge construction technology has been continuously upgraded, and large-span bridges, such as Hong Kong's Tsing Ma Bridge, the Hangzhou Bay Sea Crossing Bridge, Italy's Messina Strait Bridge, and Canada's Golden Ears Bridge, have been put into use successively. However, as the service lives of bridges increase, changes in external environmental conditions, such as wind loads, geology [1], temperature, and humidity [2], will gradually reduce the durability and safety of bridge structures. Therefore, in order to understand the current health status of bridges in a timely manner, many large-span bridges are equipped with health monitoring systems to assess and decrease the potential bridge health risks, and extend the service life of bridges.

Unlike traditional manual visual inspection with carried devices, modern bridge health monitoring (BHM) systems reduce a significant amount of manpower and material costs used for inspections, and achieve the real-time monitoring of bridge strain, deflection, vibration, and other characteristics by installing sensors in various parts of the bridge. The monitoring system integrates functions such as data collection, health diagnosis, and damage warning, making the entire bridge structural testing process dynamic and convenient. The operation process of the traditional BHM system is shown in Figure 1. Considering the complexity and importance of BHM, scholars from various countries have paid extensive attention to it and have constantly proposed new improvement and development schemes.

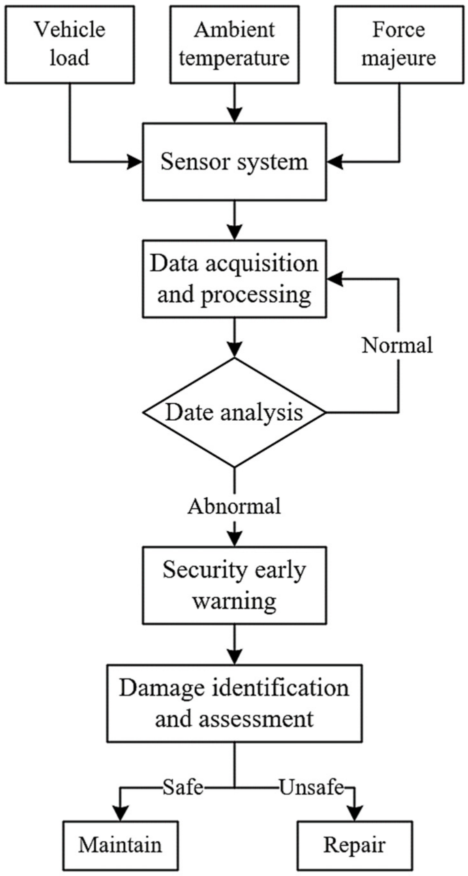

Figure 1. Flow chart of bridge health monitoring system.

Yokohama-Bay Bridge is one of the bridges in Japan with the most installed monitoring equipment. During the Great East Japan Earthquake (Mw 9.0) in 2011, the BHM system on this bridge collected comprehensive response data sets from the earthquake's foreshocks, main shock, and aftershocks, providing important evidence for scientific research [3]. The significance of BHM lies in its ability to predict various events that may occur on bridges, apart from force majeure, to protect life and property safety. In 2007, due to design defects and neglect of stress conditions, the I-35W Mississippi River bridge in Minneapolis collapsed during rush hour, causing serious casualties [4]. In the same year, the Jiujiang Bridge in Guangdong, China, collapsed after being hit by a sand-hauling ship [5], indicating that bridges should be continuously monitored for important waterways and warnings should be issued when danger approaches. Reviewing past bridge collapse accidents can explain the importance of BHM in bridge engineering from another perspective.

In the early development of BHM, due to immature analysis techniques and the scarcity and inaccuracy of monitoring equipment, it often led to mismatched predictions and actual results, which posed serious safety hazards to bridges. Rizzo and Enshaeian [6] reviewed the research undertaken in the past 20 years on bridges with BHM installed in the United States. Among these bridges, the North Halawa Valley Viaduct had installed over 200 sensors at various locations on the bridge during the construction period for monitoring multiple parameters. A subsequent study [7] found that the long-term deformation results obtained using general prediction methods for the bridge differed significantly from the actual deformation. This difference was confirmed to be due to the neglect of concrete shrinkage and creep. Bazant et al. [8] studied creep and shrinkage prediction models such as those from the American Concrete Institute, Japan Society of Civil Engineers, and CEB-FIP Model Code. The results showed that these widely used models at the time generally underestimated bridge deflection. In addition, BHM faces many challenges, such as fatigue and corrosion evaluation, scour effects, etc. [9], requiring further research to propose better solutions.

In this paper, we provide an overview of the research progress in BHM technology in recent years and summarize the research on the damage identification of bridge structures. The structure of the following content is as follows. In Section 2, sensor monitoring technology and computer vision-based monitoring technology are reviewed separately, with a focus on an overview of fiber optic sensing and wireless sensing methods. In Section 3, data processing methods including data preprocessing, data denoising, and data reconstruction for signal data collected by sensors are reviewed. In Section 4, a review of the research conducted by various countries on early warning systems for BHM is presented. In Section 5, the recent advances in vibration-based and non-destructive testing-based damage identification methods are summarized. Finally, we summarize the research progress in the different directions mentioned above. We introduce some representative literature on BHM technology in this paper, aiming to provide a clear framework for future research.

2. Monitoring Technology

During the service life of bridges, unfavorable status changes often occur due to internal structural characteristics and external environmental effects, which pose safety hazards. Failure to detect these unfavorable changes in a timely manner may lead to catastrophic consequences and result in a significant loss of life and property. BHM systems use a large number of sensors installed at optimal positions on a bridge through reasonable methods [10,11], to monitor and provide feedback on its structural response, structural defects, and external environment in real-time. For cracks, peeling, deformation, rusting, and other structural issues, image-based methods are used for detection [12–14]. In this section, current research hotspots in sensor systems and computer vision-based monitoring methods will be reviewed.

2.1. Sensor Monitoring Technology in BHM

During the service of bridges and other building structures, the important components of the structure are prone to failure due to the impact of severe working conditions. Given the problems of inaccurate measurement accuracy, poor stability, short service life, and the high energy consumption of traditional sensors, researchers have been seeking improvement methods over the past two decades. Fiber optical sensors (FOS) have emerged as an excellent sensing technology due to their inherent advantages such as small size, light weight, strong anti-electromagnetic interference capability, corrosion resistance, and embeddability [15–17].

2.1.1. Fiber Optic Sensors

In the early 1960s, fiber optics were studied and used in optical transmission systems [18]. With the wide application of information transmission technology based on optical transmission, people begin to focus on the study of material properties that affect optical transmission. In this case, optical measurement systems continue to make progress. A typical example in BHM is that FOS can be installed on the surface of rebars or embedded in pre-drilled holes to monitor the strain, temperature, and vibration of rebars. In 2019, Abdel-Jaber et al. [19] proposed a method for monitoring prestress loss in prestressed concrete structures using FOS to provide a formal method for on-site evaluation. In the case of the Streicker Bridge strain sensor on Princeton University campus, they used the FOS strain measurement to study strain change at the centroid of the composite section. They reported that it has the advantage of being able to obtain accurate measurements when the temperature changes, and that it shows a wide range of applicability. The numerical results show the feasibility of FOS in the measurement of prestress damage.

FOS can be divided into two types, distributed and discrete, based on whether they can monitor continuously with increasing distance. Distributed fiber optic sensors (DFOS) are a major research focus for achieving sensing measurements for thousands of measurement points using a single fiber optic cable [20]. According to different principles of light scattering, DFOS can be divided into the following three categories: DFOS based on Brillouin scattering, DFOS based on Raman scattering, and DFOS based on Rayleigh scattering [21–23]. The comparison of different types of DFOS is shown in Table 1. In the field of BHM, the sensing technology based on Brillouin scattering has been applied more widely.

Table 1. Classification and comparison of DFOS.

Classification	Test Method *	Measurement Distance and/or Spatial Resolution	Disadvantage	Application
Rayleigh scattering	OTDR	Tens to hundreds of kilometers	Low spatial resolution	Vibration sensing
	OFDR	Resolution at mm level	Short measuring distance	Distributed temperature and strain sensor
Raman scattering	ROTDR	Ten kilometers	Low spatial resolution	Distributed temperature sensor
	ROFDR			
Brillouin scattering	BOTDR BOTDA BOFDA	Dozens of kilometers, 0.4–0.5 m resolution Resolution at cm level	A complex system, long test time	Distributed temperature and strain sensor

* OTDR: optical time domain reflection; OFDR: optical frequency domain reflection; OTDA: optical time domain analysis; OFDA: optical frequency domain analysis.

In 2017, Scarella et al. [24] proposed a structural health monitoring method for cable-stayed bridges based on the dynamic distributed sensing of bridge deck strains. To detect the location and size of the damaged cable, a formula was developed using the dynamic distributed sensing capability of Brillouin scattering optical time domain analysis (BOTDA), and the relationship between the strain redistribution on the deck of the cable-stayed bridge and the tension loss of the single cable was established. The applicability of this method was demonstrated in a scaled model test case of a cable-stayed bridge in the laboratory. In 2019, Oskoui et al. [25] used FOS based on Brillouin scattering to monitor and normalize the distributed strain of trucks relative to the theoretical influence line of the bridge during multiple locations. In addition, they introduced the damage index in a method to identify microcracks. The author reports the test results on the concrete box girder bridge, which proves the effectiveness of this method. In 2022, Bertulesi et al. [26] proposed a hybrid structural health monitoring (SHM) system based on Brillouin DFOS. They introduced vibrating wire (VW) extensometers and temperature probes into the monitoring system and compared and corrected the data of the DFOS and extensometers according to the temperature effect. In the case study of a water penstock bridge, it was confirmed that the strain time series collected by the two methods have a good match. The results showed that the application of Brillouin DFOS to the SHM system under complex conditions is a cost-effective and good performance scheme.

2.1.2. Wireless Sensor Technology

The monitoring system of long-span bridge will produce a large number of monitoring data sets every day. If all the sensors used to collect this data were traditional wired sensors, the cost would undoubtedly be huge, which provides a demand for the research and application of wireless sensors. A wireless sensor network (WSN) is a network form that combines a large number of sensor nodes in the monitoring area into a network system through wireless communication technology, as shown in Figure 2.

The WSNs deployed on bridges are characterized by a layered network communication protocol consisting of five layers, namely the physical layer, data link layer, network layer, transport layer, and application layer. The physical layer facilitates signal monitoring, transmission, and reception, with the design goal of minimizing energy loss while maximizing link capacity [27]. The data link layer primarily enhances the functionality of transmitting raw bits from the physical layer [28]. The network layer is responsible for packet routing and network interconnection [29], forming the foundation of data transmission. The transport layer provides reliable and efficient means for data transmission. Finally, the application layer transforms data into usable information for the physical world. Rupani and Aseri [30] proposed an improved WSN transport layer protocol based on the pump slowly, fetch quickly (PSFQ) protocol. They analyze the proposed protocol in terms of average delay and average fault tolerance, and the results are better than the ordinary PSFQ protocol.

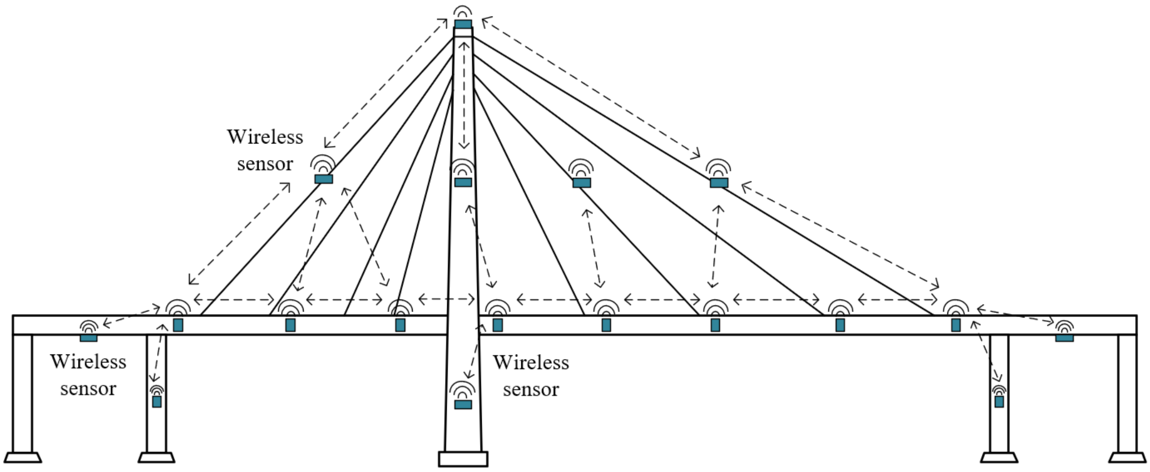

Figure 2. WSN-based bridge health monitoring system [31].

In SHM, a WSN is more convenient to deploy and maintain, and has a lower cost. However, the wireless characteristics of the network also bring a series of new challenges to researchers, including communication delay and security, effective routing, and network scalability. Among numerous wireless protocols, WiFi (IEEE 802.11), Bluetooth (IEEE 802.15.1), and ZigBee (IEEE 802.15.4) are suitable examples for use in WSNs. Among them, WiFi has a longer transmission distance and an extremely fast transmission rate, but also consumes a considerable amount of energy. Therefore, without special modification methods, WiFi technology is not suitable for WSNs that require long-term monitoring. Like WiFi, Bluetooth also faces the dilemma of high power consumption, even though its performance is good. In the existing research [32], ZigBee has been used to design low-power low-rate wireless personal area networks (LR-WPAN) that meet the requirements of WSNs. Wijetunge et al. [33] summarized the advantages of using ZigBee in the underlying wireless communication technology of WSH, and also pointed out its drawbacks, such as the idle listening mechanism with additional energy consumption. Krishnamoorthy et al. [34] developed a reservation-based protocol based on the existing IEEE 802.15.4 standard, which provides a selectable solution for addressing the additional energy consumption of ZigBee. In addition, a medium access control (MAC) protocol can reduce the energy consumption of sensor nodes during idle time, but it has the disadvantage of communication delay, which is solved well by a B-MAC protocol. Bdiri et al. [35] introduces an Energy Harvesting System in wireless sensor nodes and reduces unnecessary energy consumption that may occur through the B-MAC protocol. The combination of the two technologies greatly reduces the energy consumption of sensor nodes.

Ayyildiz et al. [36] developed sensor mote hardware to trigger a piezoelectric sensor with lead zirconate titanate material, which had excellent fracture detection performance. They used the network interface of the system to remotely analyze the data collected after triggering the piezoelectric sensor. The results showed that the newly developed system can successfully detect cracks that threaten the safety of the structure. Huang et al. [37] proposed a method based on WSNs to measure the micro-vibration of a bridge piers during extreme weather conditions and frequent natural disasters. They first used a WSN to collect data signals at different locations on a pier. Then, the Fast Fourier Transform (FFT) and Welch methods were used to process the signals to obtain the pier vibration frequency data. At the same time, the measured natural frequency was used as a calibration parameter to establish a finite element model to estimate the scouring depth. This method provides a practical tool for dealing with the risk of bridge collapse caused by pier scouring. In a study on the method of estimating bridge cable tension, Zhang et al. [38] proposed a fully automated and robust identification method based on an Xnode wireless sensor system. The method was validated by Jindo Bridge data. The numerical results showed that the natural frequency and order of the bridge cable obtained by this method and the Matlab method were basically consistent, and the predicted tension results matched the actual data very well, which can effectively realize the automatic estimation of cable tension.

Wireless sensor networks are widely used in civil SHM because of their excellent data collection capability, convenient installation, and low cost. To realize their long-term operation, some scholars have studied the power reduction methods of WSNs. Figure 3 illustrates a simple WSN model in which sensor nodes are linearly arranged and each sensor collects data within the distance between adjacent nodes.

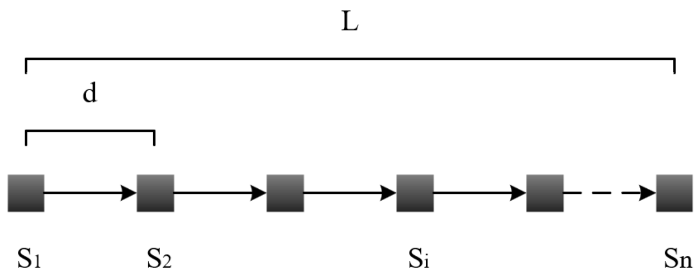

Figure 3. A linear network model comprising n relay nodes (from S_1 to S_n).

Assuming that the model considers transmission power as the only parameter, the energy E required to transmit a data packet at a rate of R bits/s along the distance d can be expressed as [39]

$$E = \varepsilon_{amp} R d^k \tag{1}$$

where ε_{amp} is the energy dissipated in the transmitting radio-frequency (RF) amplifier and k is the path loss exponent, which normally ranges from 2 to 6 [40]. It is apparent from the formula that, under certain environmental conditions, we can control the energy consumption of the WSN by altering the type of RF amplifier or changing the layout of the sensor network, including modifying the position and spacing of the sensors.

As more innovative sensing technologies, including WSNs, are continuously being applied to SHM, it is worth noting how to provide an optimized solution for determining the number and placement of sensors to maximize their information collection capability and address energy consumption issues. Generally speaking, the sensor node localization methods in WSNs can be classified into non-distance-based and distance-based methods. In non-distance-based methods, a validated and effective approach is to identify the high-connectivity anchors for each sensor and use the centroid of the anchor points as its location [41]. Additionally, reliable sensor localization can be achieved by measuring various parameters such as the pairwise time-of-arrival (TOA), the time-difference-of-arrival (TDOA), the received signal strength (RSS), and the angle-of-arrival using distance-based algorithms [42]. In their research on sensor location optimization, Meo and Zumpano [43] proposed two comparative standards using vibration displacement as the dataset. The first standard is the mean square error between the FE model and the cubic spline-interpolated mode shapes, and the second standard is the information content of the sensors, which shows the signal strength obtained by different placement schemes and their noise resistance ability.

Hussein et al. [44] studied two optimization schemes of node layout. They compared the life of WSNs under the two schemes with the results obtained by the common equidistant layout method, and obtained the optimal node layout scheme of the sensor network, which can reduce energy consumption by 20% and extend life by 140%. Sarwar et al. [45] designed an event-based WSN to reduce the power consumption of sensor nodes that capture random events. In addition, the system can be easily configured to existing wireless sensor platforms. The current consumption before and after activating the system on a commercial wireless platform verified the ultra-low power consumption of the system. Considering WSNs with multi-type sensor clusters, Hao et al. [46] developed a cluster-based network optimization algorithm to improve the energy utilization efficiency of the network and extend the network lifetime. On this basis, they obtained the coefficient of variation of the estimated parameters based on Bayesian inference, which can be used as a global measure to evaluate the accuracy of the sensor network. In another study, Hao et al. [47] added the genetic algorithm (GA) strategy based on the previous research to improve the computational efficiency of this method. The performance of the proposed method was verified in two WSNs. In a study on the application of WSNs, Deng [48] studied the network layout of wireless sensors and applied a WSN to the dynamic response test of bridges under train effects. They tested the layout effect and detection capability of the WSN through a case study comparing wired sensors. The results showed that the WSN had a reliable dynamic response detection performance and an effective network layout. In practical applications, wireless measurement is often limited by transmission distance. Hou et al. [49] introduced a low-power Internet of Things method to detect bridge displacement in wireless sensor systems. This system can greatly reduce the limit of the transmission distance, accurately collect displacement data, and send it to the server for remote analysis and visual operation via a web interface. Based on the experimental and field test results, the effectiveness of the system was verified.

In most cases, monitoring data in BHM systems are sensitive and confidential. Therefore, more secure routing protocols are needed for data transmission. AnandaKrishna et al. [50] proposed an improved encryption algorithm, called the R-XOR algorithm, to address data security issues in WSNs. The security performance of the proposed algorithm was validated using Brute Force attacks, and it has a higher throughput and lower overhead. To address the issue of WSN node failures, Krishnan and Thangavelu [51] proposed an early prevention method (EPM). They studied various aggregation functions and models in a WSN and found that weighted bucketing has a higher working level, significantly filtering out irrelevant information collected by sensors, and effectively solving the problem of node data loss.

The main challenge in applying WSNs to BHM is the high energy consumption during the wireless long-distance transmission of sensor data. On the one hand, the limited battery capacity of wireless sensor nodes restricts their transmission power, and on the other hand, the transmission coverage area is related to the transmission power. Therefore, in order to avoid wasting resources and time on repeated battery replacement for wireless sensors in the future, research on reducing WSN energy consumption and maximizing its lifespan needs to be further developed.

2.2. Computer Vision-Based Methods

For decades, computer vision-based methods and image-processing technology have been widely applied and studied in many fields [52–60]. Due to its advantages of non-contact, long distance, low cost, and high resolution, this new measurement technology has been applied to the study of SHM by many scholars. In 2017, Khuc and Catbas [61,62] reported a new framework for SHM systems. They proposed a method for measuring displacement and vibration based on non-target computer vision, and then developed a camera calibration method to address the unavailability of traditional calibration standards. The effectiveness of the proposed method was verified by comparing the measurement results with the traditional sensors in a four-span bridge model and stadium structure. In

2019, Bao et al. [63] combined computer vision with deep learning (DL) to detect anomalies in monitoring data. When the data was visualized, the signal was converted into an image vector to input the deep neural network. In 2022, Ma et al. [64] studied displacement estimation techniques at different sampling frequencies. They combined a hybrid computer vision algorithm with a Kalman filter and used a new calibration algorithm to estimate the high-sampling displacement. The error of the estimated displacement in the experimental verification was less than 1.5mm. This technique has practical application potential in long-term structural displacement monitoring. In 2023, Cardellicchio et al. [65] proposed an automated method for identifying defects in RC bridges using computer vision. They first trained a neural network using images of defective areas from existing RC bridges. Additionally, they introduced the Class Activation Maps (CAMs) method in Explainable Artificial Intelligence (XAI) technology to explain the recognition results of the deep learning method and achieve the highlighting of specific defect types.

Recently, some researchers have begun to integrate vehicle load measurements into SHM systems using computer vision technology. Khuc and Catbas [66] developed an identification framework with a new damage indicator using computer vision-based vehicle load modeling and image-based structural identification. The damage recognition capability of the framework was verified on a laboratory model. Jian et al. [67] combined the influence line theory with computer vision technology in their study. They proposed a traffic sensing method to collect traffic load information. The effectiveness and accuracy of this method were verified in the system analysis of a continuous box-girder bridge. This method is expected to be widely used in bridge weigh-in-motion (WIM) systems. Hou et al. [68] studied the method for accurately associating traffic load with bridge response. In their proposed framework, a computer vision approach based on DL was used to accurately identify trucks from field images. The framework was applied to a 20-mile highway corridor to verify the correlation between bridge response peak and measured truck weight, based on one year's measured data. In practice, the existing identification methods usually require prior information of the road to locate the traffic load, which is tricky in some cases. Chen et al. [69] studied the position relationship between the camera and passing vehicles. They proposed a recognition method that computes the spatiotemporal information of vehicles by mathematically processing camera locations. The reliability of this method was verified by laboratory tests and field measurements. Ge et al. [70] improved the existing traffic load monitoring (TLM) technology for the entire bridge deck. They developed a dual-target detection model based on DL to identify vehicle features captured by cameras. In addition, they proposed an optical geometry model to accurately estimate vehicle position. The results from on-site data validation showed that the proposed method has excellent real-time capability, accuracy, and lighting robustness. Figure 4 illustrates the on-site hardware system for monitoring bridge traffic load, which mainly consists of the pavement-based weigh-in-motion (WIM) and the video surveillance system.

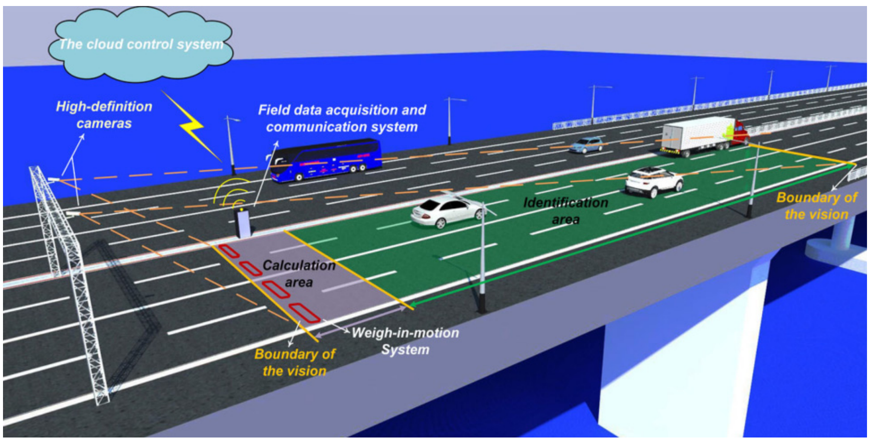

Figure 4. On-site hardware layout of the traffic load monitoring (TLM) system [70].

Jana and Nagarajaiah [71] developed a video-based technique for measuring stay-cable tension. They used a mobile handheld camera to record cable vibrations at a distance and incorporated a series of image-processing techniques to eliminate interference from the camera's motion. Then, the real-time frequency was estimated according to the time history of cable vibration, and finally, the real-time tension was determined. Based on this study, Jana et al. [72] proposed a framework based on video measurement to reduce the estimation error of cable tension. The effectiveness and reliability of the proposed method were verified by comparing it with the actual tension of the Fred Hartman bridge in Texas.

WSNs provide a convenient and reliable data monitoring tool for BHM systems, which can solve the layout and installation problems of traditional wired sensors. However, in order to avoid the loss of monitoring data during wireless transmission, research on wireless communication technology should continue. As a non-contact monitoring scheme, computer vision-based technology has been applied to the monitoring of structural vibration and displacement as well as traffic load, and has shown outstanding performance.

3. Data Processing Methods

In the previous section, we summarized the current popular sensor monitoring techniques and computer vision-based monitoring techniques for BHM data collection and their applications. In this section, we will review and discuss recent research in monitoring data processing.

3.1. Data Preprocessing

Under the influence of the uncertainty of the BHM monitoring environment, sometimes the data collected on site are unbalanced and inadequate, which leads to large errors in the bridge health assessment results, resulting in huge losses [73,74]. Therefore, to make the subsequent evaluation more accurate, it is necessary to preprocess the data collected by sensors. In 2019, Zhao et al. [75] proposed a framework based on a multi-source fusion positioning system. In this framework, a big sensor data preprocessing (BSDP) scheme, including extraction, acquisition, and transmission, is proposed to solve the problem of large amounts of data. Multi-source sensor data sources include WiFi, fingerprint, accelerometer, gyroscope, magnetometer, etc. To improve the efficiency of data transmission, they used compression sensing technology to compress the data. Experimental and simulation results demonstrated the effectiveness of this BSDP scheme. In 2021, Wan et al. [76] proposed a data enhancement model based on the generative adversarial nets to expand the existing monitoring data of bridges. They reported that the model generated new monitoring data through learning coupling among bridge monitoring factors. The simulation results showed that the bridge monitoring data generated by the model was real and effective, through which the performance of the bridge health assessment was improved. In a study on the compression and smoothing of data streams, Debski et al. [77] introduced an algorithm with an adaptive search space and a special space reduction technique, aiming to provide an efficient method for processing sensor data in Internet of Things devices, health monitoring systems, autonomous vehicles, and robots. The numerical results showed that the proposed algorithm had lower errors and higher compression ratios than the reference algorithm.

When cracks or even fractures appear in materials, local energy quickly concentrates, and when it reaches a threshold, acoustic emission (AE) signals can be generated. By analyzing the characteristic parameters of AE signals, the state of the material can be determined. Xin et al. [78] successfully used deep neural networks to construct the relationship between the scalograms of AE signals and the state of bridge cables. In addition, the experimental results demonstrate that, as two kinds of sensors with different resonant frequencies, the R6I-AST type of sensors are more suitable for detecting the break inside the cable than the R3I-AST type of sensors. Li et al. [79], in a study of the acoustic emission signals of three bridges, proposed an acoustic emission signal segmentation algorithm to solve the problem that BHM data occupied a large amount of data storage space. The analysis results showed that the algorithm can not only effectively save the data storage space, but also accurately extract the noise signal to determine the filtering threshold.

Regarding the preprocessing methods for monitoring data, three points can be summarized: (i) we can compress the raw data to improve the transmission efficiency; (ii) we can also expand the monitoring dataset through data generation models to provide more evidence for bridge health assessment; (iii) establishing the relationship between monitoring data and structural status is always beneficial for the next step of assessment.

3.2. Data Noise Reduction

Removing the adverse effect of noise on the signal is extremely crucial to the whole signal-processing process. In recent years, many scholars have studied new methods to deal with noise in BHM. Embedded rail systems (ERS) in rail transit can significantly reduce the impact of noise generated during traffic operation [80], and some scholars consider applying it to bridges. To popularize the application of ERS, Stancik et al. [81] studied the interaction behavior between ERS and its substructure. They proposed a numerical model to simulate this interaction behavior and optimize the evaluation results of the ERS–bridge interaction using a negative feedback approach. Koh et al. [82] introduced the characteristics of ERS to the study. They highlight the contribution of ERS in solving vibration and noise problems that can improve the performance of existing plate girder bridges. By comparing the measured data of two plate girder bridges, it has been proved that ERS can reduce the vibration and average noise of the bridge.

Cheng et al. [83] proposed a blind source separation technique based on a second-order blind recognition algorithm to reduce the impact of noise signals on bridge damage identification. They verified the accuracy of the proposed algorithm in damage frequency identification by comparing the FFT method in the numerical experiment. Liu et al. [84] studied the denoising method of the dynamic deflection signal of the bridge. They first decomposed the dynamic deflection of the bridge obtained by the monitoring system into a series of intrinsic modal functions (IMF), and then removed the noisier part according to the algorithm. The remaining IMF were reconstructed as new signals, and the residual noise was further eliminated by a morphological filter method. Simulation and field experiment results show that this method has remarkable denoising ability. Wang et al. [85] proposed a denoising method combining wavelet threshold denoising and Hilbert–Huang transform (HHT) to overcome the serious influence of noise on first-order natural frequency. Jiang et al. [86] studied the Hong Kong–Zhuhai–Macao Bridge's immersed tunnel and developed an improved wavelet threshold denoising (WTD) method to eliminate the noise in the concrete strain data. They used the sparse index and coefficient of variation to select the best wavelet basis and optimize the threshold, and finally obtained a satisfactory denoising effect. Ravizza et al. [87] discussed the advantages and disadvantages of two denoising technologies based on discrete wavelet transform (DWT) and singular value decomposition (SVD). In both the time and frequency domains, two kinds of response signals were synthesized for testing. The results showed that both of the two denoising methods can effectively purify seismic response signals, while, for the processing of environmental vibration signals, the denoising method based on DWT exposed defects. Shang et al. [88] developed a deep convolutional denoising autoencoder to reconstruct relational functions from data corrupted by noise to extract the desired features for damage recognition. Park et al. [89] introduced a generalized sidelobe canceller into the dual-sensor noise reduction method. This method realized two-stage noise reduction through a filter and determinant-based controller. Compared with other mainstream methods, the experimental results showed that the proposed method was superior.

The wavelet threshold method is a popular and efficient signal denoising method. Figure 5 illustrates the denoising results of the monitoring data on the Hong Kong–Zhuhai–Macao Bridge's immersed tunnel using the WTD method. As shown in Figure 6, this method mainly consists of three components: signal decomposition, threshold processing, and signal reconstruction. By selecting the most suitable wavelet base, decomposition level, threshold value, and threshold function, the noise reduction effect can be improved.

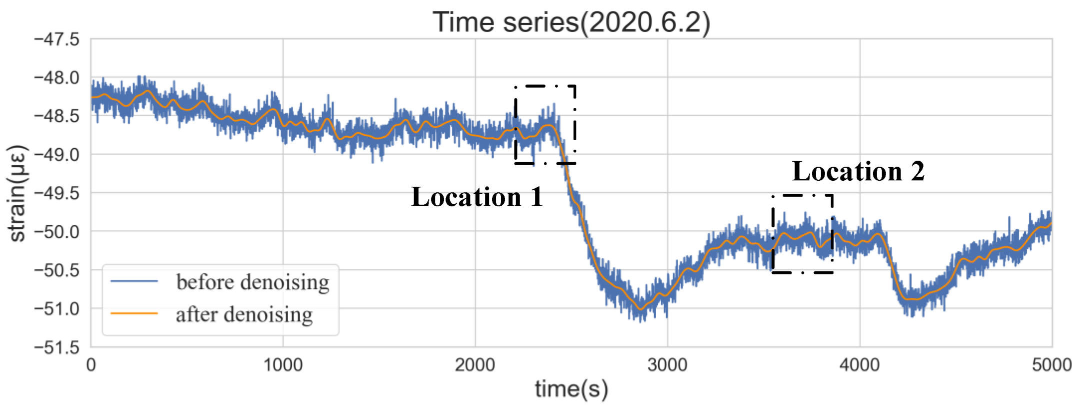

Figure 5. Time series of the monitoring data before and after WTD [86].

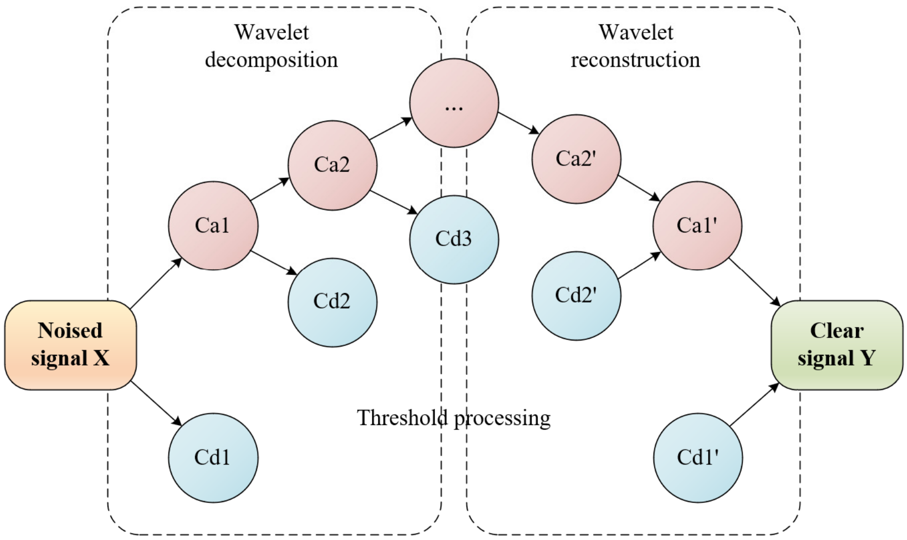

Figure 6. Process of WTD (Ca: the low-frequency information; Cd: the high-frequency information).

3.3. Data Reconstruction

In a typical BHM system, data are often missing due to sensor failures, or data are incomplete due to sensor signal loss during transmission. When the data loss rate is too high, the health assessment of the structure cannot be carried out properly, which may lead to serious consequences. To ensure the reliability of the monitoring data used for analysis, many studies have been carried out.

Due to its excellent ability in processing large amounts of data and extracting features, DL has been applied in various fields such as medical treatment, computer vision, finance, and transportation [90–93]. Wang et al. [94] proposed a data recovery framework based on a deep neural network to recover long-term missing wind data from bridges. The framework divides data recovery into two tasks and takes advantage of a free access database in Europe to obtain wind data for learning. In addition, they used a time–frequency cross-domain loss function for training to enhance the reconstruction performance of the wind speed signals. In the case study of Sutong Bridge in China, the feasibility and effectiveness of the proposed framework were verified.

The convolutional neural network (CNN), as a representative algorithm in DL, has become a research hotspot in the field of SHM recently. Fan et al. [95] developed a new CNN structure to recover lost vibration data in SHM. They introduced the bottleneck architecture and skip connection in a CNN to construct the nonlinear relationship between the damaged data signal and the intact signal. The effectiveness and robustness of the proposed method were verified by comparing the measured data of the pedestrian bridge. Furthermore, they studied the case of a high data loss rate, and the proposed method still showed excellent data recovery ability. Oh et al. [96] studied a training method for CNN. They first used healthy monitoring data to build a CNN model. They then deliberately excluded responses from specific sensors and used the response data from the remaining sensors as input to the neural network. Through numerical and experimental studies, it was verified that the trained CNN can effectively recover the excluded sensor data. Jiang et al. [97] reported a neural semantic recovery framework that transformed data recovery into a conditional probability modeling problem. They used the semantic features of the vibration data as conditions and the CNN as a feature capture tool. In addition, they proposed a new perceptual damage function to improve the efficiency of the network. The results of the case study showed that the framework had splendid data recovery accuracy even when the loss rate was high.

In 2014, inspired by game theory, generative adversarial networks (GAN) were developed to generate high-resolution images [98]. As one of the most successful generative models in DL, GAN has developed many variants over the years and has been used in the field of SHM. Yoon et al. [99] proposed a missing data interpolation method based on the non-supervision GAN framework to recover the missing deflection data of BHM systems. They used a thin neural network and a generator–discriminator structure to form the data recovery framework. By analyzing the measured data of a highway and railway bridge, the advantages of the proposed method over the traditional GAN model in execution speed and reconstruction accuracy were verified. Zhang et al. [100] introduced the Bayesian dynamic regression method to improve the GAN model. They reported that the method can achieve the ability to model the collected data set and make missing predictions. The validity of the model was verified by using the engineering data of Jiangdong Bridge in Hangzhou. Wang et al. [101] proposed a new conditional generative adversarial network (CGAN) to improve the generative adversarial interpolation network (GAIN) [99]. They extracted the implicit category information contained in the data set and used it to generate a classifier to evaluate and optimize the interpolated data. The experimental results showed that this method was superior to the GAIN algorithm, even in the case of a high data miss rate.

GAN contains a generative model G and a discriminant model D, and the two models constantly update each other's parameters until they reach the optimum in training. In fact, the operation of the GAN model is a minimax iterative process about G and D. CGAN is a common extension of GAN. It adds certain conditional information y before the generative model and discriminant model in GAN. Figure 7 shows the structure of a simple conditional adversarial network. In the study by Wang et al. [101], y is set as a category label. Under such conditions, the objective function of the optimization problem is as follows:

$$\underset{G}{min}\underset{D}{max}V(D,G) = E_{X\sim P_{data(x)}}[logD(x|y)] + E_{X\sim P_z(z)}\left[\log\left(1 - D\left(G(x|y)\right)\right)\right] \tag{2}$$

where $V(D,G)$ is the objective function of the CGAN; x and y represent the training data and the input condition data, respectively; and $P_z(z)$ is the prior noise variable. $G(z;\theta_g)$ is used to learn the distribution p_g of training data x, ranging from $P_z(z)$ to data space. The output of discriminator $D(x;\theta_d)$ is used to represent the probability that x came from the training data, from which we can judge whether x can be identified as p_g.

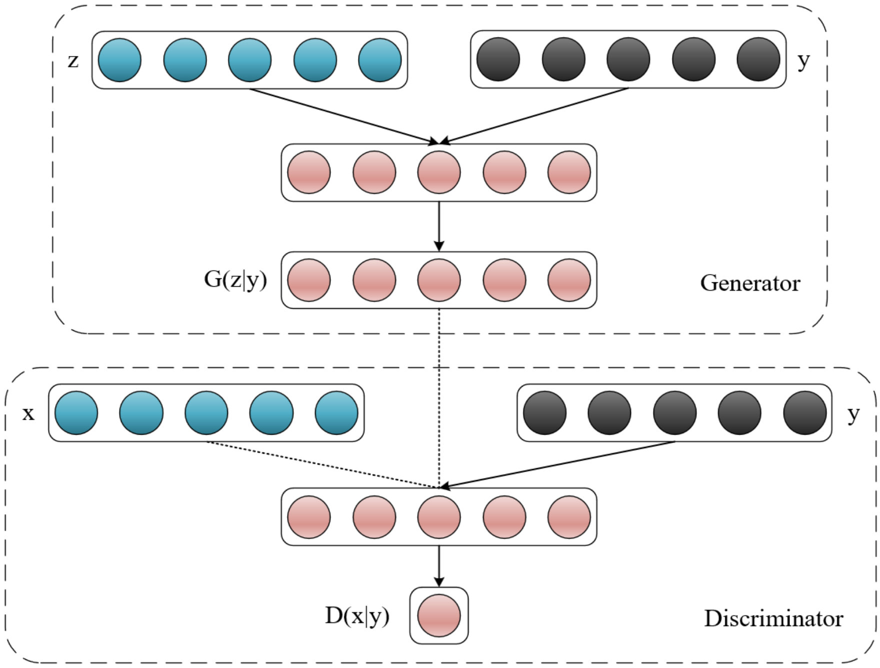

Figure 7. Conditional adversarial net [102].

In 2019, Jeong et al. [103] studied temporal correlations among the sensor data. Before this, most sensor data recovery methods only focused on the spatial correlation among data. They proposed a data-driven bidirectional recursive neural network for data reconstruction. Sensor data from the Telegraph Road Bridge in Michigan were used to verify the accuracy of the proposed method in data reconstruction. Du et al. [104] developed a response recovery method for heterogeneous structures. They reported that this approach took into account not only the temporal and spatial dependencies of the data but also the dependencies between heterogeneous structural responses. Furthermore, they proposed a parallel optimization method to optimize the parameters of the network. Three months of monitoring data on a bridge were collected to train and test the proposed method. The results showed that this method can interpolate the missing data accurately, especially when the data loss rate was high. Ju et al. [105] introduced a recursive neural network when studying the temporal correlation of data, and built a framework for abnormal data recovery. The monitoring data of the Bund Bridge in Ningbo, China were used to verify the accuracy of their framework.

Niu et al. [106] developed a spatiotemporal graph attention network for restoring missing data. The network uses the inherent temporal and spatial dependencies of sensor networks for modeling to obtain temporal and spatial features to reconstruct missing signals. They also discussed the recovery accuracy of multi-source and single-source data fusion. In the application of the cable force data recovery of long-span cable-stayed bridges, the model showed satisfactory accuracy. Zhang et al. [107] proposed two matrix decomposition (MF) methods based on autoregression (AR) for data interpolation and structural response prediction. In the first approach, the authors developed a time regularizer and combined it with the standard MF formula. In the second approach, they introduced an additional AR-based matrix. The accuracy and reliability of the proposed method were verified by the SHM data set collected in the field.

4. Early Warning Systems

In the previous section, we summarized the research on the data processing methods of BHM in recent years from three aspects: data preprocessing, noise reduction, and loss reconstruction. In this section, we will review the recent research progress in early warning systems in BHM.

Aiming to save on the cost of system operation, a command from the BHM system is usually required before implementing SDI. Therefore, in BHM, the study of early warning systems is also crucial. It needs to be emphasized that, in the actual monitoring process, issuing warnings and identifying anomalous structural states are closely related but are not necessarily at the same level of operation. The warning system may not need to precisely locate and quantify damage like the damage identification system does. Instead, it often provides warnings of different levels by setting one or more warning thresholds. Zhao et al. [108] studied the vortex-induced vibration (VIV) phenomenon of long-span bridges in a special wind environment. A method based on multisource load response data was proposed for the early warning of VIV. Chen et al. [109] conducted a numerical and case study on the early warning method of the Hong Kong–Zhuhai–Macao Bridge's immersed tunnel. Based on monitoring data with wavelet threshold denoising, an autoregressive integrated moving average (ARIMA) was used for future data prediction. They developed a hierarchical early warning system that proved to be effective at grading the detected anomalies. Deng et al. [110] developed a platform based on Revit to realize visual warnings and the integrated management of monitoring information. They associated monitoring data with a BIM model through a virtual sensor system and then imported it into Revit. Based on monitoring data during typhoon Haikui, Ye et al. [111] developed a machine learning model, called the integrated girder vibration indicator. The indicator takes wind data as the input and girder and tower vibrations as the output. When the prediction results exceed the normal threshold, it will give an early warning.

Other scholars have considered temperature conditions. Zhao et al. [112] studied the early warning method of deflection change in railway bridges caused by temperature and train load. They used the monitoring data and the mutual update of the train–bridge dynamic model to monitor the bridge deflection behavior and, at the same time, determined the early warning threshold of it under the combined action of the two factors. Huang et al. [113] introduced the temperature-displacement relationship (TDR) model to predict the performance degradation of bridge bearings for the first time. They used SBL for model parameter identification to solve the problem of sparse model parameters caused by the insensitivity of bearing displacement response to temperature. Ren et al. [114] applied TDR to the abnormal boundary condition warning of the bridge. The high anomaly detection rate and low false detection rate of the proposed method were verified by using the actual girder end displacements from a large-span suspension bridge in China. Li et al. [115] studied the early warning method of cable force anomalies in cable-stayed bridges, considering the change in structural temperature. A baseline model of the frequency–temperature relationship (FTR) was established to give early warning when the predicted cable force error occurred. Wang et al. [116] studied anomaly warning methods under the influence of various environmental factors and proposed an environment–frequency relation model based on local linear regression. The effectiveness of the proposed method was verified on a cable-stayed bridge.

Cusson et al. [117] investigated the application of an interferometric synthetic aperture radar (InSAR) for visualizing and alerting unexpected bridge displacement. The validation was conducted on Jacques Cartier Bridge and Victoria Bridge, located in Canada. The proposed tool from this study is expected to be used as a future platform for bridge displacement assessment and warning. Selvakumaran et al. [118] used an improved InSAR method to analyze satellite observation scenes before the collapse of Tadcaster Bridge in the UK, demonstrating that the method can serve as an effective warning system for monitoring bridges at risk of erosion. Lim et al. [119] proposed a measurement system for the vibration characteristics of suspension bridges based on low-frequency cantilever-based fiber Bragg grating accelerometers (CFAs) and verified the accuracy of the system on a suspension bridge in Malaysia. Additionally, the system can trigger early damage warnings when detecting changes in vibration characteristics. Among the US bridges with BHM systems installed [6], multiple types of sensors were installed on the Sunshine Skyway Bridge, and data other than the vibration of the cable-stayed bridge were used to predict the bridge's motion as caused by temperature and wind direction changes, while determining the threshold for triggering alerts. After discovering cracks on the Carroll Lee Cropper Bridge in the US, micro-crack gauges were installed in the direction of the cracks. The researchers determined the threshold for crack expansion and developed a warning system to alert when the crack exceeds the threshold.

Different warning systems set warning thresholds based on different parameters, such as wind-induced vibration, beam deflection and displacement, cable tension, etc. The significance of the warning system is that when the monitoring data reaches or exceeds the threshold value, the regulator can be alerted very soon after the occurrence of an anomaly, so that subsequent inspections can be carried out. In addition, the temperature effect of the structure should always be taken into account, as it may cause unnecessary warning. Table 2 summarizes all the literature reviewed in this section, listing the specific bridges examined in each study and the methods applied in the early warning system.

Table 2. Cases of early warning systems for bridges.

Bridges	Authors	Feature and/or Application
Yingwuzhou Yangtze River Bridge, China	Zhao et al. [108]	Vortex-induced vibration warning
Hong Kong–Zhuhai–Macao Bridge, China	Chen et al. [109]	ARIMA and hierarchical warning system
Ge Xian Bridge, China	Deng et al. [110]	Visualization warning based on Revit
Sutong Bridge, China	Ye et al. [111]	Integrated girder vibration indicator
Nanjing Dashengguan Yangtze River Bridge, China	Zhao et al. [112]	Early warning of beam deflection under temperature and train coupling
Nanjing Dashengguan Yangtze River Bridge, China	Huang et al. [113]	TDR model for early warning of performance degradation of bridge bearing
A large-span suspension bridge, China	Ren et al. [114]	TDR model for early warning of abnormal boundary conditions of bridges
A single pylon cable-stayed bridge, China	Li et al. [115]	FTR for early warning of abnormal cable force
A cable-stayed bridge, China	Wang et al. [116]	Local correlation model between frequency and multiple environmental factors
Jacques Cartier Bridge and Victoria Bridge, Canada	Cusson et al. [117]	InSAR for visualization warning
Tadcaster Bridge, England	Selvakumaran et al. [118]	Improved InSAR for bridge erosion warning
A suspension bridge, Malaysia	Lim et al. [119]	A system for measuring vibration based on CFAs
Sunshine Skyway Bridge, America	Rizzo and Enshaeian [6]	Early warning when temperature and wind direction changes abnormally
Carroll Lee Cropper Bridge, America	Rizzo and Enshaeian [6]	Early warning of crack propagation

5. Damage Identification Methods

The SDI of bridges is one of the most important parts of the whole health monitoring system. The accuracy of damage identification has a direct impact on the safety of bridge structures, which has been of great concern to scholars all over the world in the past decades. Four levels of SDI were proposed by Rytter [120] in 1993. Levels 1 to 4 are as follows: judging the existence of damage, locating the damage, quantifying the severity of damage, and predicting the service life of the damaged structure. In this section, we will review some recent studies focusing on SDI in BHM.

5.1. Modal Parameter-Based Methods

Once the structure is damaged, the change in stiffness will inevitably lead to changes in the structural modal parameters. Therefore, according to the used modal parameters, SDI methods can be divided into four categories: natural frequency-based, mode shapes-based, curvature mode shapes-based (CMS), and methods using both frequency and mode shapes [121]. However, due to the unqualified sensitivity of natural frequency to local damage, the method using only natural frequency as an index can generally only achieve Level 1 SDI, which has been phased out in recent years. Among the other three methods, the mode shape-based and CMS-based methods are the focus of recent research.

5.1.1. Mode Shape-Based Methods

Chaudhary et al. [122] applied the concept of the spectral element method to the derivation of the mode shape expression to establish the mathematical correlation between the mode shapes of damaged and healthy structures. The numerical results of a fourteen-storey shear building and a six-storey laboratory building model showed that the proposed method was effective in quantifying damage. Duvnjak et al. [123] proposed a new method to identify damage in plate-like structures. They established a damage index, namely the mode shape damage index (MSDI), based on the difference between the modal displacements before and after the structure was damaged. Experimental and numerical studies on reinforced concrete slabs showed that the MSDI was reliable in locating damage. However, the proposed method did not perform well in identifying the severity of the injury, and further research was needed. Abdulkareem et al. [124] developed a simple and rapid SDI technique. Using the method of interval analysis, they deduced the interval conditions of each section of the beam according to the mode shape of the beam structure in a damaged and a healthy state. The possibility of damage was defined in each beam segment, and the product of it and the mode shape increment was taken as the damage measurement index. The numerical simulation results showed that the proposed method can identify the given damage rapidly and accurately.

Passing vehicles will elicit responses from the bridge structure, so sensors can be installed on vehicles to monitor the response data. The modal parameters with a high spatial resolution can be extracted from the vehicle response. Recently, some scholars have paid attention to this. He et al. [125] developed a two-stage bridge damage detection method based on the mode shape estimated by moving vehicles. They first identified the damage location using the damage location index defined in the regional mode shape curvature (RMSC). Then, the relationship between damage degree and RMSC was established in a finite element simulation. Numerical and experimental examples demonstrated the effectiveness of the proposed method. Under the condition of meeting the accuracy requirement, the method can locate and quantify the damage by using only one sensor response, which proves that the indirect recognition method has a good application prospect. Yang et al. [126] improved the indirect SDI method utilizing vehicles. In their study, the filter in the traditional vehicle scanning method (VSM) was replaced by a self-made filter. Compared with the previous VSM, the mode shape extracted by this method was more obvious. Therefore, this improved VSM did not need to establish an additional damage index, which greatly reduced the post-processing workload.

5.1.2. Curvature Mode Shape-Based Methods

Ahmad et al. [127] studied the application of the CMS method to multiple damage detection. They introduced a gapped smoothing method to minimize noise. The effectiveness of the proposed method in damage location was proved by a comparison with previous studies. Bagherkhani et al. [128] improved the CMS approach using the distributed genetic algorithm. The results of several laboratory tests showed that the proposed method can complete tasks of Level 3 SDI under various noise levels. Pooya et al. [129] introduced a difference indicator, which came from the difference between a CMS and a CMS estimation of the damaged structure, to detect the location of the damage. This method provides a new way to detect damage in structures that lack health monitoring data because it does not require complete structural data. However, only the first mode was studied. For higher modes, the computational cost and time of this method will increase.

5.1.3. Mode Parameter Combined Methods

To overcome the difficulty of SDI based solely on mode shape or frequency, some scholars have studied methods of combining multiple modal parameters. From a statistical perspective, Doehler et al. [130] proposed two subspace-based methods that utilize natural frequencies and mode shapes to consider uncertainty factors such as noise, limited data, and non-stationary excitations. The proposed methods were validated to achieve Level 3 SDI in the damage test of the S101 Bridge in Austria. Dahak et al. [131] proposed a method combining natural frequency variation and CMS for damage detection. They used two vectors, the measured frequency change value and the curvature mode of the intact structure, to plot the damage position and damage coefficient function. The practicability of the proposed method was verified by a numerical simulation and a laboratory model of a cantilever beam. From the perspective of the neural network, Zhong et al. [132] took mode shape and mode curvature differences, respectively, as the input of CNN training samples to study their damage location accuracy. The results showed that the damage location accuracy was higher when the mode shape was used as the input. Chinka et al. [133] conducted theoretical and experimental modal tests for crack identification in cantilever beams by using CMS and natural frequency. Firstly, the governing equation of the transverse motion of the beam was established, and the frequency and mode shape of the damaged beam were calculated. Then, the first four CMS were drawn using these modal parameters. Similarly, the crack location and damage coefficient were obtained from the intersection of the curves. This method had received ideal recognition results in the test.

In most cases, the modal parameters of the structure are the basis for SDI. To maximize the effect of SDI, modal parameters must be extracted with greater precision and utilized in a more complete manner. The aforementioned SDI methods based on modal parameters are summarized in Table 3.

Table 3. Modal parameter-based SDI methods.

Mode Parameter	Authors	Feature and/or Advantage	SDI Level	Application
Mode shape	Chaudhary et al. [122]	Spectral element method	1–3	Fourteen-story shear building and experimental six-story building model
	Duvnjak et al. [123]	MSDI	1, 2	Experimental RC plate
	Abdulkareem et al. [124]	Interval analysis	1 and 2	Numerical beam
	He et al. [125]	Moving vehicle estimation	1–3	Experimental modal
	Yang et al. [126]	Improved VSM	1 and 2	Experimental modal
Curvature mode shape	Ahmad et al. [127]	Gapped smoothing method	1 and 2	Numerical plate
	Bagherkhani et al. [128]	Distributed genetic algorithm	1–3	Numerical beam and frame structure
	Pooya et al. [129]	No need for complete data	1 and 2	Numerical and experimental modals
Multiple modal parameters	Doehler et al. [130]	Frequency and mode shape	1–3	S101 Bridge in Austria
	Dahak et al. [131]	Frequency and CMS	1–3	Numerical and experimental beam
	Zhong et al. [132]	Mode shape and mode curvature difference	1 and 2	Numerical steel truss
	Chinka et al. [133]	Frequency and CMS	1–3	Numerical and experimental beam

5.2. *Finite Element Model Updating Methods*

Another method of damage identification is to establish the finite element model (FEM) of the complete structure and obtain the normal structural parameters. Then, compare it with the measured data from the damaged structure to find the difference among the structural parameters, which is finally used to detect the damage. However, most of the time, the FEM cannot completely replace the actual structure. There are differences between the structural features obtained by analysis and the actual features, which will lead to inaccurate damage detection. To narrow the gap between the model and the actual structure, a series of finite element model updating (FEMU) methods are proposed.

5.2.1. Gaussian Process-Based FEMU

The Gaussian process (GP) is a random process in statistics. The conceptual basis of GP begins with a reference to a simple multivariate Gaussian distribution, and marginalization and conditioning are its two fundamental operations. GP is a powerful model that can directly model functions to generate non-parametric models [134]. Therefore, it has the unique advantage of efficiently quantifying a variety of uncertainties.

Moravej et al. [135] proposed a new probabilistic framework for structural performance evaluation, using the first-order reliability method (FORM) and GP to consider various sources of uncertainty. In this framework, the GP surrogate model was replaced by a finite element model with an associated discrepancy function. They also proposed a modular Bayesian approach (MBA) for placing such GP models. The feasibility of the proposed frame was verified on a laboratory box girder bridge, and the results showed that the proposed method can accurately detect the decrease in structural performance and the increase in failure probability. Xia et al. [136] used a GP metamodel to replace the 3D finite element model of the bridge for updating. They first studied the thermal effect mechanism of the bridge deck and established the relationship between the longitudinal boundary stiffness (LBS) and the structural temperature. The GP metamodel was then used to map the relationship between LBS and longitudinal displacement. The analytical value of the longitudinal displacement of the proposed method was compared with the measured results of the Jiangyin Suspension Bridge. The results showed that the identified LBS had sufficient accuracy, and the analytical value of the longitudinal displacement was in good agreement with the actual value. Lin et al. [137] also used a GP model to replace FEM in a study of model updating methods based on influence lines. In a case study of a long-span suspension bridge, this substitution improved the efficiency of the iterative optimization of boundary condition estimates.

5.2.2. Bayesian Methods-Based FEMU

Zhou et al. [138] studied the vibration-based model updating method for the damage detection of a steel truss bridge. Field tests were carried out under five operating conditions, and they used the fast Bayesian FFT method to identify the modal characteristics. In the three bridge models established, the modal characteristics updated by this method are consistent with the actual data. With more prior information, the damage detection capability of this method was verified. Zhang [139] introduced a transfer learning (TL) technique into the Bayesian model updating (BMU) method, which can bridge the gap between the numerical model and the real structure. In addition, numerical and experimental studies showed that TL enables BMU to recognize injury severity despite modeling errors. Chen et al. [140] proposed a two-stage method for bridge FEMU. The proposed method combined a radial basis function (RBF) neural network and Bayesian theory. The feasibility of this method was verified by a series of numerical and laboratory experiments.

5.2.3. Nonlinear Model Updating Methods

In a study to evaluate the damage and residual performance of piers after earthquakes, He et al. [141] established a nonlinear section element model and proposed a two-stage model updating technique. In this method, the maximum and minimum strain of the section are used as updating parameters to update the damage parameters of nonlinear material models. Zheng et al. [142] developed a new nonlinear FEMU method. This method can be used to evaluate the degradation of structural strength and stiffness in the time domain. In the shaking table test of a cable-stayed bridge, the proposed method can accurately identify the damage and predict the seismic response. Based on a nonlinear

FEMU method, Liu et al. [143] identified the bond-slip and core concrete parameters of a full-scale RC bridge column and achieved the identification of damage on the bridge column by utilizing the variation of these parameters. Lin et al. [144] proposed a nonlinear FEMU method based on a time history analysis. The feasibility and accuracy of the proposed method were verified on the scaled structure of Sutong Bridge in China.

5.2.4. Other FEMU Methods

Figueiredo et al. [145] proposed a hybrid technique that combines model-based and data-based SDI methods. In the proposed method, real monitoring data under normal conditions are fused with data obtained from FEM under extreme environmental conditions and input into machine learning algorithms for SDI. The reliability of this method was verified using monitoring data from the Z-24 Bridge. Vahidi et al. [146] proposed a FEMU method that combined multiple meta-heuristic optimization algorithms for damage detection. They first used a genetic algorithm (GA), particle swarm optimization (PSO), and artificial bee colony (ABC) algorithms, respectively, for FEMU in numerical simulations. Then, the damage detection performance of each algorithm was compared, and the PSO and ABC methods were selected as a combination in this method due to their better performance. Perera et al. [147] proposed a roaming damage method (RDM) in FEMU to identify local damage in large bridges. The reliability of the proposed method was verified in the case study of the I-40 bridge in New Mexico. Alpaslan et al. [148] introduced a mathematical statistical method, namely the response surface (RS) method. They reported that the optimal identification results between experimental and numerical analyses can be obtained by using this method in the updated FEM.

It can be seen that the FEMU-based SDI methods have made new research progress in different directions in recent years, showing a bright application prospect. However, as mentioned above, these studies are limited in some ways. The FEMU method depends on the modified parameters of the model. Although some scholars have taken into account the uncertainty of these parameters [135,137,139,149] and the nonlinearity of the structure [141,142,144], in the FEM analysis of complex structures, faced with a large number of correction parameters, a repeated calculation process will lead to a slow updating process or deviation. The substructure method can decompose the whole model correction process into several independent blocks to avoid the double calculation of local damage. It may serve as an auxiliary method to solve these problems. The FEMU methods mentioned in this section are summarized in Table 4.

Table 4. Finite element model updating methods.

Method	Feature and/or Advantage	Application
Gaussian Process	First-order reliability method and modular Bayesian approach	Experimental box girder bridge [135]
	Temperature consideration and longitudinal boundary stiffness	Jiangyin Suspension Bridge [136]
	Boundary conditions consideration and influence lines	Large-span suspension bridge [137]
Bayesian Inference	Transitional Markov chain Monte Carlo sampling and fast Bayesian FFT	Steel truss bridge [138]
	Transfer learning is used to bridge the bias	Numerical and experimental models [139]
	Radial basis function	Numerical and experimental models [140]
Nonlinear Model	Transform to solve constrained optimization problems	Numerical model [141]
	Evaluate strength and stiffness degradation in the time domain	Experimental RC bridge [142]
	Considering bond-slip	A full-scale RC bridge column [143]
	Time history analysis- and cluster computing-aided PSO algorithm	Numerical model [144]
Others	Fusion of real data and simulation data	Z-24 Bridge [145]
	Particle Swarm and Artificial Bee Colony Algorithms	Numerical model and a high-rise building [146]
	Roaming damage method and perceptron regression neural network	I-40 bridge in New Mexico
	Response surface	Numerical and experimental models [148]

5.3. Optimization Algorithm-Based Methods

Due to the complexities of bridge structures and the rise of long-span bridges, ordinary algorithms have been unable to handle the task of increasing bridge monitoring data. Therefore, many optimization algorithms have been applied to bridge damage identification. This section mainly reviews meta-heuristic algorithms and artificial neural network (ANN) algorithms in optimization algorithms. The Bayesian method will be detailed in Section 5.4.

5.3.1. Meta-Heuristic Optimization Algorithm

The meta-heuristic optimization algorithm is a kind of method to solve the optimal solution by simulating nature. Starting from the genetic algorithm (GA) [150], the developed meta-heuristic algorithms have been widely used in the optimization of various practical problems. Yang et al. [151] improved the three basic operators in the classical GA and introduced an objective function based on the dynamic response of the bridge under train load to solve the problem of damage identification when the model element division is different from the actual damage location. Huang et al. [152] proposed a hybrid optimization algorithm based on PSO and cuckoo search (CS). The temperature was parameterized in the study. The numerical model and real bridge test results showed that the hybrid algorithm can distinguish the deviation caused by the temperature effect from the actual damage and achieve Level 3 SDI. Tran-Ngoc et al. [153] studied the local minimum problem of ANN and used CS to improve the training parameters to solve this problem. Huang et al. [154] proposed a double jump strategy in bare bones particle swarm optimization (BBPSO) algorithm, and the results showed that this method can effectively improve the efficiency and robustness of BBPSO in SDI. Ding et al. [155] introduced a clustering strategy into the original Jaya algorithm and optimized the update equation for the best solution. The objective function of the proposed I-Jaya algorithm was obtained by sparse regularization and Bayesian inference. Considering significant noise and modeling errors, the reliability of the algorithm was proved by numerical and laboratory studies.

Huang and Lei [156] developed a hybrid moth–flame optimization algorithm based on a variety of optimization methods. In numerical and experimental tests, the hybrid algorithm showed a better global search ability and was feasible in practice. Su et al. [157] introduced a strategy for eliminating low-adaptive individuals in the directional bat algorithm (DBA). When elimination is complete, a new random individual will be created, which induces an increase in population diversity. The experimental examples showed that this improved DBA algorithm can accurately identify damage and has good robustness. Huang et al. [158] used a modal flexibility curvature overlay to accurately locate the damage, and then determined the damage degree by an enhanced whale optimization algorithm (WOA). The experimental results showed that the proposed method was effective without noise, but it was slightly sensitive to noise when quantifying the damage degree. Later, Huang et al. [159] proposed a new objective function based on fractal dimension (FD) for WOA. In the simulation test, WOA could effectively identify the damage degree under noise conditions. Table 5 shows the optimization algorithms reviewed in this section.

Table 5. Optimization Algorithms.

Authors	Method	Feature and/or Advantage	SDI Level
Yang et al. [151]	Improved GA	Enhanced local optimization capability	1–3
Huang et al. [152]	PSO–CS	Consider temperature variations and better optimization performance	1–3
Tran-Ngoc et al. [153]	ANN–CS	Avoid local minimum	1–3
Huang et al. [154]	Improved BBPSO	Avoid local minimum	1–3
Ding et al. [155]	Improved Jaya algorithm	Improved objective function based on sparse regularization and Bayesian inference	1–3

Table 5. *Cont.*

Authors	Method	Feature and/or Advantage	SDI Level
Huang and Lei [156]	Chaotic moth–flame–invasive weed optimization	Strong global search ability and high convergence efficiency	1–3
Su et al. [157]	Modified DBA	Elimination strategy to increase the diversity of the population	1–3
Huang et al. [158]	Enhanced WOA	Objective function based on flexible matrix	1–3 *
Huang et al. [159]	FD–WOA	Good anti-noise ability	1–3

* Quantization effect is affected by noise.

5.3.2. Artificial Neural Network

As a powerful intelligent computing tool, an ANN has unique advantages in solving large complexity problems. ANNs can be effectively applied to SDI after training. Azam et al. [160] studied the damage caused by load changes and proposed a neural network training method based on proper orthogonal decomposition (POM). A supervised learning method was used to distinguish POM changes caused by injury. In the experiment, the authors successfully identified the damage caused by the train load on the railway truss bridge. Malekjafarian et al. [161] used vehicle response to train ANN. They obtained the predicted error value based on the actual response compared with the predicted vehicle response. Then, the error distribution variation obtained by GP was used to identify the possible damage. Nguyen et al. [162] used transmissibility functions as the input data of ANN in the research on damage identification in Ca-Non Bridge in Vietnam. They used simulated vehicle response data from the bridge to verify the effectiveness of the method. Zhang et al. [163] developed a simple one-dimensional CNN and established three independent acceleration databases for training. It is worth noting that the proposed CNN can still accurately identify structural state changes without any processing of the training data. As one of the representative algorithms of deep learning, CNN's general architecture is given in Figure 8.

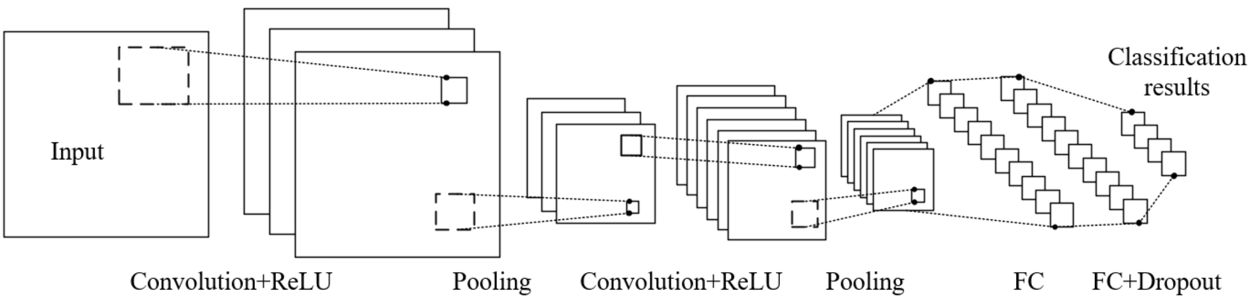

Figure 8. Architecture of the CNNs (ReLU is the activation function; FC is the fully connected layer).

In vibration-based SDI, the change of structural modal characteristics is an important damage index. Nick et al. [164] proposed a two-stage method for damage identification in steel beam bridges. Firstly, the damage was located based on modal strain energy (MSE) and the damage index was obtained simultaneously, which was then used as an input parameter to train the ANN. Jayasundara et al. [165] improved the damage index of the input ANN. They first trained two ANNs using damage indexes based on modal flexibility and MSE, respectively, and then fused the training results of the two networks. The damage identification capability of the proposed method was verified in an experiment of a long-span arch bridge. Tan et al. [166] proposed a new damage detection method for steel–concrete composite bridges. For steel beam units, they used damage indices based on MSE in ANNs, and for bridge decks, they used a loss index based on modal flexibility in ANNs. Nick et al. [167] studied the anti-noise performance of three SDI methods based on MSE, modal flexibility, and modal curvature. They then trained an ANN on the modal flexibility-based approach that performed best in anti-noise tests. A network with good noise resistance and damage quantification ability was obtained. Jayasundara et al. [168] used principal component analysis (PCA) to compress the frequency response data and feed it back to the ANN for damage prediction. Padil et al. [169] proposed to apply the non-probabilistic method to PCA to reduce errors caused by various uncertainties and improve the efficiency of the frequency response data.

Aiming to better avoid the limitations of using solely ANNs in SDI, some scholars combine the meta-heuristic algorithm with an ANN in their research. Tran-Ngoc et al. [153] introduced the CS algorithm in the study of improving the ANN's training parameters. Before the network was generated, the appropriate weight of the training parameters was found through CS to narrow the deviation between the real output and the expected output. Khatir et al. [170] introduced the butterfly optimization algorithm (BOA) into an ANN and developed a BOA–ANN hybrid model for crack detection. In addition, they have improved ANN's training process. Xiang et al. [171] combined the improved hunter–prey optimization algorithm with a CNN to solve the optimization problem of the objective function in CNN.

5.4. Bayesian Methods

Damage identification in civil structures is confronted with the challenges of measurement noise and modeling errors, which may lead to inaccurate identification results. For example, the presence of measurement noise may mask small structural changes caused by damage. Therefore, deterministic methods may fail in practical applications. To overcome these challenges, many researchers have proposed probabilistic damage recognition methods. Among these methods, Bayesian inference has received much attention and has developed many practical methods in SDI today. Ni et al. [172] proposed a probabilistic method to assess the state of bridge expansion joints and issue damage alarms. In their established Bayesian TDR model, model parameters are treated as random variables, which can eliminate uncertainty factors. They also reported that the method can quantify predicted uncertainty. The effectiveness of the method was validated by utilizing monitoring data from the Ting Kau Bridge in Hong Kong.

Rogers et al. [173] developed a Dirichlet process (DP) Gaussian mixture model for training algorithms in the absence of SHM data. In laboratory and field tests, this DP hybrid model showed a strong Bayesian nonparametric clustering ability. Kullaa et al. [174] introduced Bayes' rule into virtual sensor networks and proved that this method had better signal denoising performance than real sensors. Hou et al. [175] considered both uncertainty and temperature change in sparse Bayesian learning (SBL). They established a functional relationship between vibration characteristics, temperature, and damage, and then took the temperature into account through a quantitative relationship. Zhang et al. [176] constructed the likelihood function and prior probability density function of the Bayesian model based on FFT data. The feasibility of this method for damage detection was verified in numerical and laboratory studies. Arangio and Beck [177] proposed a two-step strategy based on Bayesian neural networks for the damage assessment of long-span suspension bridges. They first improved the neural network model based on the probability logic method, and then used the framework to detect and quantify bridge damage successively.

Chen and Wang [178] developed a probabilistic fatigue damage model based on Bayesian learning for the wind-induced fatigue damage assessment of long-span bridges. By utilizing the wind information recorded by the SHM system, the Bayesian learning method was applied to determine the probability of fatigue damage in local components. The applicability of the proposed method is verified in the study of the Tsing Ma suspension Bridge in Hong Kong. Li et al. [179] studied a model simplification technique, through which damage detection based on SBL can be carried out under the condition that the measured degrees of freedom were limited. Li et al. [180] reported a combination of the Bayesian theory and perturbation methods to detect structural bearings. The posterior probability density function of the damage parameters was obtained by using the Bayesian damage detection theory, and the calculation cost was saved by using the matrix perturbation method. Wang et al. [181] proposed a new SBL-based approach, which was driven by probabilistic data. Firstly, damage-sensitive frequency bands were established based on monitoring data to construct the damage index. The predicted value of the SBL regression reference model was then used to judge the damage and the Bayes factor was used to quantify the damage degree. Finally, the feasibility of the proposed method was verified by using real bridge monitoring data.

As a method of deriving sparse solutions in the context of regression and classification, SBL takes uncertainty into account by hyper-parameters with explicit physical meaning. The automatic updating of hyper-parameters solves the problem of regularization parameter selection in sparse recovery.

In Bayesian computing methods, there is a highly important method to calculate the expectation of a posterior distribution, namely the Markov Chain Monte Carlo (MCMC) method. Ding et al. [182] adopted the Metropolis–Hastings (MH) sampling of the MCMC method to solve the complex expressions in the damage assessment model. The applicability of this method to damage assessment was verified in the case analysis of a bridge hanger. Luo et al. [183] introduced the PSO algorithm into the MH sampling method, and called it the MH–PSO hybrid MCMC sampling method. Numerical damage recognition results showed that the method had enhanced sampling efficiency and damage recognition ability. Xu et al. [184] focused on damage detection in latticed shell structures. The proposed damage diagnosis indexes were analyzed by the MCMC method to obtain the frequency distribution histogram of the posterior probability. The finite element analysis results showed that this method provided a reliable tool for damage diagnosis under the premise of considering the uncertainty in the monitoring process. Luo et al. [185] proposed an improved method for the MH algorithm to facilitate the rapid selection of proposal distribution in MCMC methods and to enhance computational efficiency. The proposed method employs an interchain communication mechanism among the simple population and utilizes a tuning-free strategy to simplify the algorithm. The numerical and experimental results demonstrate that the proposed method exhibits faster convergence than traditional algorithms, even when the population size is relatively small.

5.5. Methods under Varying Temperature Conditions

In the BHM process, not only damage will cause changes in the dynamic characteristics of the structure, but also environmental uncertainties, especially varying temperature. Figure 9 illustrates the variation of natural frequency with temperature in a study. If these effects cannot be eliminated, the accuracy of the damage assessment cannot be guaranteed. Huang et al. [186] proposed a GA-based damage detection technique, in which the damage parameters affected by temperature changes are variables in the numerical model. Experiments were conducted on a three-span continuous beam and a two-span steel grid, achieving Level 3 SDI while considering the variations in material properties and boundary conditions with temperature changes. Bhuyan et al. [187] analyzed the sensitivity of the parameters affected by temperature in FEM, and proposed a correction method for modal parameters that consider the temperature field. The experimental result showed that the SDI performance was improved after the parameters were ameliorated by this method. In the previously mentioned PSO–CS algorithm [152], the effect of temperature was eliminated by establishing a functional relationship between ambient temperature and the elastic modulus of materials. Sun et al. [188] introduced a new concept, equivalent damage load (EDL), to approximate local damage treatment. In the simulation experiment of a two-span continuous bridge, it was proved that this method can distinguish between the structural response caused by damage and temperature effectively. Hou et al. [175] studied the relationship between temperature and natural frequency in SBL. To solve the problem that it was difficult to directly establish the SDI baseline when considering the temperature gradient, Wah et al. [189] obtained the damage reference value based on a single temperature condition. Damage was identified by the deviation of the measured value from the reference value. The effectiveness of this method was verified in model and field tests. Cai et al. [190] studied the change rule of the natural vibration frequency of RC simply supported beams with varying temperatures, and the experimental results showed the linear negative correlation between the natural frequency and temperature in a specific temperature range.

Wang et al. [191] firstly applied PCA combined with a Gaussian mixture method (GMM) to bridge damage detection under varying temperatures. All the damage features were projected into both principal and non-principal component directions; then, a PCA based method was used to extract the loss features in the non-principal component, and GMM was used to classify the damage features and the effects of temperature in the principal component. In addition, they found that there was not always a linear relationship between the natural frequency of the actual bridge and the ambient temperature. Wah et al. [192] refined the above approach to address the piecewise effects from changing temperature conditions. They first used PCA for the observations, then applied GMM to the first principal component and temperature conditions. The results of Z24 Bridge in Switzerland demonstrated the validity of this method, but it was only limited to Level 1 SDI. Zhu et al. [193] combined ICA with moving principal component analysis (MPCA) to identify structural anomalies under the influence of temperature. The blind source separation of thermal response was realized by ICA, and then sent to MPCA for processing to reveal abnormal changes.

Huang et al. [194] incorporated temperature change into Young's modulus of materials and proposed a mathematical model for damage identification considering varying temperatures. They used the support vector machine (SVM) to determine temperature changes and possible damage locations, and then used MF optimization methods to accurately locate and quantify damage based on the established mathematical model. The feasibility of this method was verified in the application of I-40 bridge. Sharma and Sen [195] adopted an autoassociative neural network (AANN) to isolate the damage features in the structure when the temperature changes. The inputs of the network are frequency and temperature, and the output is the predicted value of the normal frequency. According to the difference between the input and the output of AANN in each damage case, an RBF neural network was used to classify each case. Cao et al. [196] replaced the conventional finite element in the FEM with a probabilistic finite element to consider the influence of ambient temperature on the bridge FEM. They proposed a damage location method based on probabilistic features and demonstrated the effectiveness of the method through numerical simulation. Cho et al. [197] studied the change in dynamic characteristics of an RC slab bridge and a rigid frame bridge under the influence of environmental factors. Long-term monitoring results showed that temperature was the most important factor, which affected the natural frequency of the bridge. Yang et al. [198] introduced a new label for the damage characteristics caused by ambient temperature, namely, characteristics of the narrow dimension (CND). When the damage characteristics were determined to conform to the CND index, a method was proposed to detect the bridge damage under the influence of the environment. Numerical results and field examples demonstrated the effectiveness of the proposed method.

It is undeniable that temperature change is a crucial aspect among the environmental factors that affect BHM. However, research on other environmental factors is also essential in improving BHM. Gara et al. [199] investigated the influence of the soil–structure interaction (SSI) and site response on the dynamic performance of continuous viaducts. They used FEM to detect and verify the contribution of SSI in altering the dynamic response of continuous viaducts. Chaudhary [200] studied the extent to which SSI and pier column inelasticity variations affect modal parameters under different horizontal seismic excitations, aiming to provide a higher fidelity FEM. During seismic excitation experiments conducted on pile foundations established in five soil profiles, modal frequencies demonstrated a sensitivity to the effects of SSI and pier column inelasticity, which was not reflected in the mode shapes.

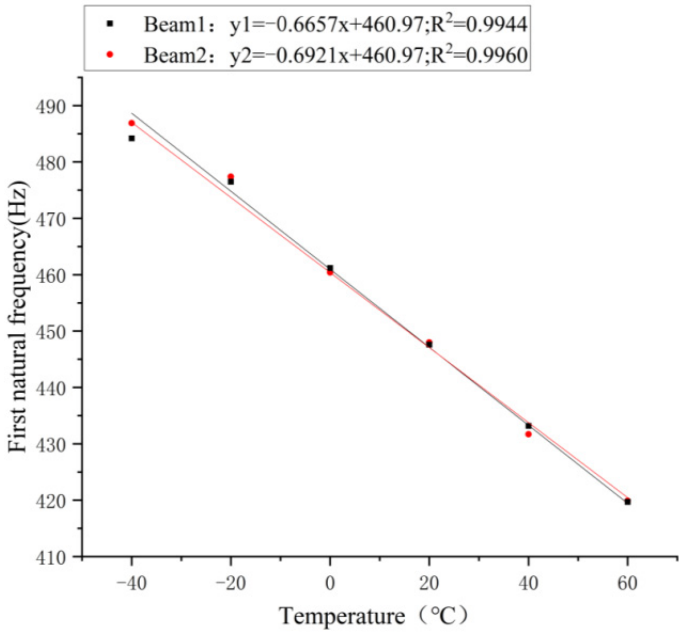

Figure 9. Relationship between the first-grade natural frequency of the No. 1 beam and the No. 2 beam with temperature change [190].

The natural frequency of structure is an important parameter in SDI, which can guide the detection and improvement of structure by reflecting its dynamic characteristics. In general, the natural frequency is related to the stiffness, mass, and boundary constraints of the structure. When the external environment affects these properties, the natural frequency of the structure changes accordingly, among which the influence of temperature is particularly significant, as shown in Figure 9. Therefore, in the process of SDI, it is necessary to distinguish between structural property changes caused by environmental variations and those caused by structural damage [201], so as to obtain more accurate identification results.

5.6. Non-Destructive Testing Methods

The damage occurring on large and complex bridges is difficult to detect through visual inspection, and in many cases, it is not feasible to conduct extensive vibration tests during the service life of the bridge to assess its health condition. Therefore, non-destructive testing (NDT) provides the possibility of extending the life of bridges equipped with BHM systems. NDT is a testing and analysis procedure designed to evaluate the quality of components, materials, or systems, and detect damage or defects in materials or structures without causing any physical damage [202]. The working principle of NDT depends on the measured parameters, structure type, and its physical properties [203].

Hafiz et al. [204] proposed a self-referencing NDT method based on pulse response testing for detecting and estimating the damage degree of RC bridge decks. Ultra-high-pressure hydro-blasting was performed on the deck, and infrared data analysis was conducted to observe potential damage. Takamine et al. [205] developed an acoustic emission monitoring method for detecting RC bridge decks, and they used the method to study acoustic emission signals caused by heavy rain, which revealed severe cracking deep inside the deck, indicating the effectiveness of the proposed method. Maric et al. [206] proposed a bridge maintenance method that combines visual inspection and NDT. In tests on six bridges in Croatia, the proposed method accurately detected steel corrosion on structural elements. Ali and Cha [207] studied a damage detection method for steel components on steel bridges. They used the DL method to identify the results of infrared thermography imaging of bridges, and the proposed method accurately identified corrosion and delamination on the steel surface in 200 thermal images. Ni et al. [208] studied the application of NDT methods in detecting cable defects on bridges. They developed a quantitative identification method based on magnetic flux detection and validated and evaluated the proposed method on FEM and laboratory models. NDT appears to be the best choice for detecting ancient bridges with preservation value. Chen et al. [209] conducted damage detection research on the underwater foundation of ancient stone arch bridges in China using sonar-based technology. They first measured the riverbed terrain with a multibeam echosounder to analyze the scouring condition of the underwater foundation and then scanned it using sonar imaging technology. The results clearly showed the damage to the bridge structure underwater.

As the service life of large bridges that are already constructed continues to increase, higher demands will be placed on NDT techniques in the future. Updating existing detection methods and instruments is crucial for the development of NDT technology. The NDT methods mentioned above are listed in Table 6.

Table 6. Non-destructive testing methods.

Authors	Methods and/or Tools	Research Object
Hafiz et al. [204]	Impulse response	RC bridge decks
Takamine et al. [205]	Acoustic emission signal	RC bridge decks
Maric et al. [206]	Combine visual inspection with NDT	Steel bars on bridges in Croatia
Ali and Cha [207]	Thermal infrared imager and DL method	Steel bars on bridges
Ni et al. [208]	Magnetic flux detection	Bridge cable
Chen et al. [209]	Multibeam echosounder and sonar imaging technology	Underwater foundation of ancient stone arch bridges in China

6. Conclusions

In this paper, we reviewed some noteworthy research in the field of BHM in the last five years, covering various aspects of BHM systems, especially SDI. The contributions of the various methods mentioned in this paper have been demonstrated in laboratory and practical bridge applications. However, some methods are inevitably flawed. Our main conclusions are as follows:

(1) Compared with conventional sensors, DFOS has outstanding advantages. It can continuously measure various physical quantities (strain, temperature, cracks, etc.) of the bridge along the entire length of the fiber and monitor vehicle movement information in real-time. However, two problems should be noted when using FOS. On the one hand, during on-site installation, using bare fiber will greatly reduce its service life, while on the other hand, using protective coated fiber will affect the monitoring accuracy of certain physical quantities and result in high costs. Therefore, future research may need to focus on how to improve the durability of FOS while minimizing costs. Although WSN is a good solution to the challenges of wired sensing systems, more practical problems will be encountered when choosing the best layout due to its wireless nature. Additionally, more research is expected in the future to maximize the lifespan of WSN usage.

(2) For data preprocessing, effective compression methods and data augmentation methods have been developed for large amounts of data in the current research. In terms of the data noise reduction method, the introduction of ERS in railway transit has been proven to effectively reduce bridge vibration and noise problems, with promising applications. Secondly, discrete wavelet transform is more suitable for BHM than continuous wavelet transform due to the discreteness and limited nature of the actual monitoring data. Wavelet threshold denoising methods have also received attention, achieving good denoising effects by selecting the best wavelet basis and optimizing the threshold. In terms of data reconstruction, methods based on deep learning, especially those based on CNN and GAN, have high retrieval accuracy. However, research on the combination of CNN and GAN is still limited, and there is potential to develop better-performing data recovery models.

(3) Most research on early warning measures for bridge health is based on the dynamic response of structures. However, two case studies from Canada and England, respectively, which consider visualizing warning systems, suggest that using satellite technologies, such as InSAR, for bridge risk assessment and developing visualization platforms has great potential for application.
(4) In the decades of the development of bridge damage identification methods, many systematic solutions have been proposed, such as DL-based methods, FEMU-based methods, and Bayesian inference-based methods. The increasing number of DL models make BHM more intelligent. However, to improve the accuracy of SDI, it is advisable to combine multiple methods or avoid relying solely on monitoring data. In the FEMU method, damage identification is usually achieved by observing changes in model parameters before and after damage using the established FEM. However, when modeling errors and other uncertainties exist, the changes in modal parameters may not necessarily be caused by damage. GP has been proven to be a practical model for considering various uncertainties.
(5) Intelligent optimization algorithms transform the SDI problem into a problem of minimizing the objective function. Objective functions based on different parameters can be combined with different optimization algorithms to produce various SDI methods. Therefore, the improvement of the objective function and algorithm is a major research direction.
(6) Essentially, most existing SDI methods are based on structural vibration effects. In fact, non-destructive testing also performs well in quantifying damage and needs to be further developed and applied in the future. In addition, there is currently no universally applicable method for Level 4 SDI.
(7) Existing research has shown that temperature changes can affect structural characteristics, particularly natural frequency, which has an impact on multiple aspects of BHM. Therefore, temperature effect is a non-negligible environmental factor in future research.

Author Contributions: Conceptualization, Z.D.; supervision, M.H.; funding acquisition, M.H.; writing—original draft preparation, Z.D.; writing—review and editing, M.H., N.W. and J.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Graduate Innovative Fund of Wuhan Institute of Technology, grant number CX2022175.

Data Availability Statement: Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

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