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Review Article

# Research progress on intelligent operation and maintenance of bridges

*Wanshui Han, Gan Yang*, Shizhi Chen, Kai Zhou, Xin Xu*

*School of Highway, Chang'an University, Xi'an 710064, China*

HIGHLIGHTS

- A systematic review of intelligent operation and maintenance of bridges.
- A detailed introduction of the advanced device, technology and method.
- Comparison of traditional and intelligent operation and maintenance methods.
- Guidance for improving the advanced level of bridge operation and maintenance.

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ABSTRACT

In the context of the increasing scale of bridges and the increasing service life of bridges, it is very important to carry out efficient, accurate and intelligent bridge operation and maintenance. In recent years, advanced equipment, technology and intelligent algorithms have developed rapidly. It is necessary to apply advanced equipment and algorithms to bridge operation and maintenance business to facilitate the digitalization and intelligence of bridge operation and maintenance. To grasp the research progress on the bridge intelligent operation and maintenance, this paper summarizes the research progress in recent years from the aspects of intelligent detection equipment and technology, intelligent monitoring equipment and technology, intelligent data analysis, intelligent evaluation and early warning, and intelligent repair and maintenance. According to the review, more and more smart devices have been used to replace human beings to detect dangerous and hidden bridge components. At the same time, image processing, radar and other technologies have been used to analyze component damage more objectively and quantitatively. To solve the shortcomings of traditional sensors such as short life and low robustness, more non-contact measurement methods have been proposed. Scholars have proposed various intelligent algorithms to process the massive amount of bridge health monitoring data to improve the quality of the data. To achieve the rapid perception of bridge status and timely early warning of structural abnormalities, different from traditional theoretical calculations, scholars have tried to use data-driven methods to intelligently evaluate and early warning of bridge structural status. In terms of intelligent repair and maintenance, more intelligent algorithms have been used to optimize structural maintenance strategies and determine the best maintenance time by integrating multi-

* *Corresponding author*.
E-mail addresses: hws@gl.chd.edu.cn (W. Han), yanggan@chd.edu.cn (G. Yang), szchen@chd.edu.cn (S. Chen), kaizhou@chd.edu.cn (K. Zhou), xinxbd@163.com (X. Xu).

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source heterogeneous data. All these provide strong support for the automation, digitization and intelligence of bridge operation and maintenance.


## 1. Introduction

Bridges are the lifeline to ensure national economic development and transportation channel. How to accurately and efficiently grasp the service performance of bridges, and then realize the long-term operation of bridges, still has huge challenges. In recent years, smart devices such as unmanned aerial vehicles (UAVs) and robots, intelligent algorithms such as big data and artificial intelligence, and advanced technologies such as 5G communication and the Beidou navigation satellite system have achieved tremendous development. These have brought new opportunities for the informatization, automation and intelligence of bridge operation and maintenance (Zhang et al., 2022; Zhao et al., 2021).

At present, bridge detection mainly relies on manual detection by professionals. This method is inefficient, time-consuming, and costly. Moreover, there are uncertainties in the detection results (He et al., 2021; Zhong et al., 2019a). With the help of advanced equipment such as UAVs and detection robots, it can replace manual labor to reach various parts of the bridge. At the same time, combined with image processing, point cloud, ultrasonic and other technologies, it can conduct efficient quantitative analysis of specific damage of the bridge (Gou et al., 2020). The quasi-static displacement and dynamic response of the bridge structure can reflect the current safety state of the bridge structure to a certain extent. The traditional means of measuring the quasi-static displacement or dynamic response of the bridge structure is mainly by arranging a limited number of contact sensors at key monitoring points of the bridge structure. The economy of this kind of method is poor, the sensor needs to be calibrated regularly, and there are common problems such as short life of the sensor and low quality of the collected data (Shao et al., 2019). How to innovate the way of acquiring bridge health monitoring data with the help of intelligent equipment and advanced technology, so as to realize the long-term and effective measurement of bridge quasi-static displacement and structural dynamic response, has always been a concern for scholars (Zhou et al., 2018). In the face of the massive data accumulated by the health monitoring system for a long time, it is very important to use intelligent algorithms to detect and repair abnormal data, thereby ensuring the integrity and reliability of the data (Li et al., 2015). Integrate multi-source heterogeneous data, and realize intelligent evaluation and early warning of bridge status based on intelligent algorithms such as clustering algorithm, Bayesian reasoning, and decision tree. Using deep reinforcement learning, data-driven and other methods to realize intelligent decision-making of bridge maintenance time and strategy. All of these will effectively facilitate the realization of bridge intelligent operation and maintenance.

Based on this background, to further master the latest development of intelligent operation and maintenance of bridges, this paper systematically reviews and summarizes the research at home and abroad from five aspects: intelligent detection equipment and technology, intelligent monitoring equipment and technology, intelligent data analysis, intelligent evaluation and early warning, and intelligent repair and maintenance. These are all to promote the promotion and application of cutting-edge technologies and important achievements in bridge intelligent operation and maintenance.

## 2. Intelligent detection equipment and technology

The use of intelligent detection equipment and technology reduces human participation as much as possible in bridge detection operations, allowing intelligent bridge detection equipment to complete data collection and analysis under human requirements. While liberating inspectors from heavy repetitive labor and dangerous bridge detection environments, a more scientific and objective data processing method is used to replace human subjective organ perception, which greatly improves the efficiency and accuracy of detections. In this section, the latest progress in recent years is summarized from three aspects: intelligent detection of concrete structure damage, intelligent detection of steel structure apparent damage, and detection of key vulnerable components of bridges.

### 2.1. *Intelligent detection of concrete structure damage*

#### 2.1.1. *Crack detection*

Cracks are one of the most important demage for the durability and safety of concrete bridges. It is of great significance to accurately detect the structural cracks of concrete bridges and master the development trend of structural cracks for formulating the repair and maintenance plan of bridges and ensuring the long-term operation of bridges. Therefore, how to detect cracks in concrete bridges efficiently and accurately has always been a research hotspot of scholars. Sanchez-Cuevas et al. (2019) proposed a robotic system that utilizes unmanned aerial vehicles (UAVs) for bridge-inspection tasks. The drone is innovatively designed with a compact and lightweight multi-rotor. In this way, the ceiling effect in aerodynamics can be used to make the UAV and the surface of the bridge structure stable in contact, and then the

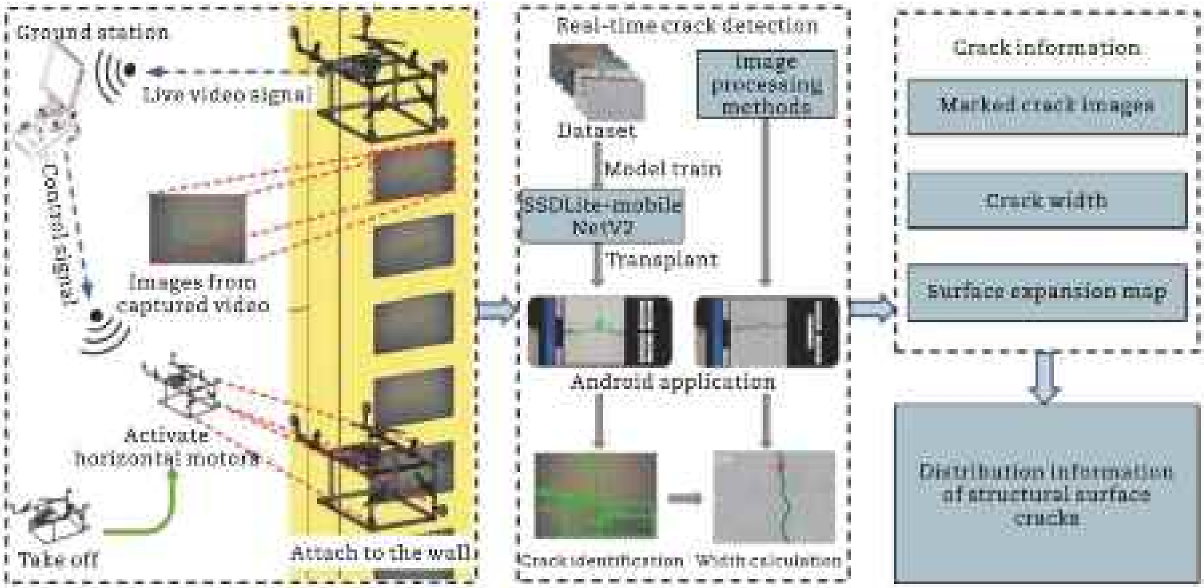


**Fig. 1 – A real-time bridge crack detection framework (Jiang and Zhang, 2019).**

approach detection can be realized. By mounting a camera on the UAV, surface defects such as cracks and damage to the structure can be identified using computer vision techniques. Additionally, the drone can be equipped with other sensors, such as ultrasonic sensors, to detect crack defects. Zhong et al. (2019b) used a UAV as a working platform to measure the object distance through an airborne laser rangefinder, and then calculated and corrected the pixel resolution of the crack image. The identification of the crack shape and width on the structure surface was realized by designing the image preprocessing program, constructing the crack shape intelligent extraction model and calculating the normal width. It still takes a certain amount of time from collecting raw information, data analysis and processing to obtaining results. To realize the integration from collecting raw data to data analysis and further improve the efficiency of crack detection, Jiang and Zhang (2019) proposed a framework for bridge crack fast detection. This method used the wall-climbing UAV system to obtain crack image information, transmitted information through wireless transmission, and then realized real-time detection of bridge cracks through convolutional neural networks (CNNs). The overall process was shown in Fig. 1. When using UAVs for bridge inspections, problems such as image distortion and positioning difficulties often occur. To solve those ubiquitous problems, Liu et al. (2020) proposed a UAV flight path and photography strategy suitable for pier crack detection. This method gave suggestions for the flight path and photography strategy of the UAV system from the three principles of clear image, sufficient overlap, and sufficient resolution. The detailed flight path was given for the circular section and the chamfered rectangular section. Then, the

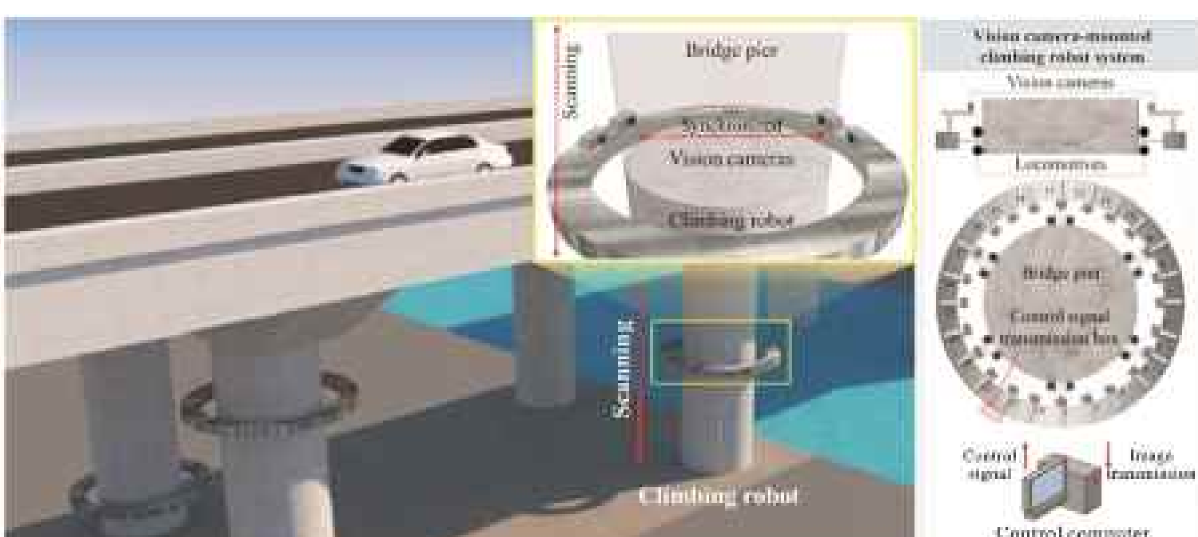


**Fig. 2 – Schematics of the vision camera-mounted climbing robot system (Jang et al., 2021).**

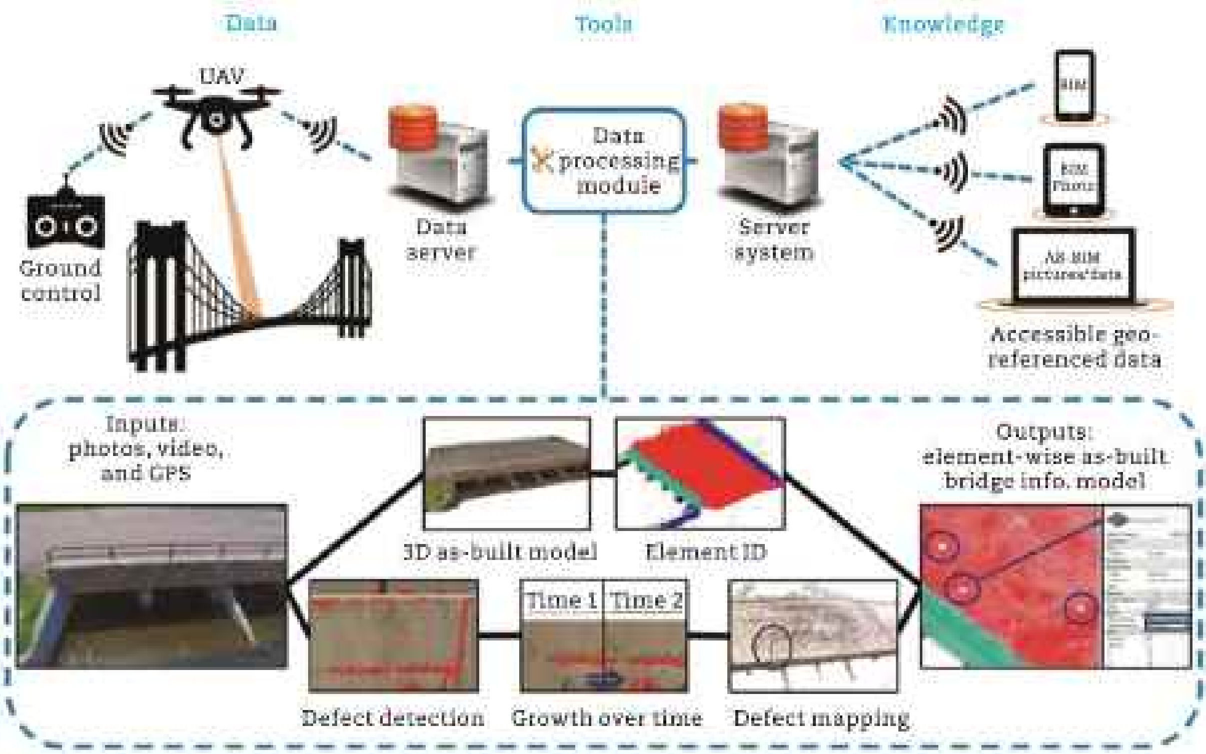


**Fig. 3 – An automated bridge detection system (Perry et al., 2020).**

digital image processing method was used to detect cracks, and the 3D scene reconstruction of the bridge piers was conducted.

How to detect and count the surface cracks efficiently and labor-savingly has always been a difficult problem for the pier which is a kind of column component. In addition to using UAVs to observe the surface of bridge piers, robots have also been tried to detect bridge piers. Jang et al. (2021) developed a ring robot composed of a camera, a climbing robot and a control computer to identify and evaluate cracks in bridge piers, as shown in Fig. 2. The image information was obtained by shooting of the camera at a close range, and then the quantitative processing for crack was realized by semantic segmentation and Euclidean distance transformation. The climbing robot was controlled by the computer to achieve the autonomous movement of the equipment.

For different crack detection scenarios, scholars have innovatively proposed different intelligent methods. Dan and Dan (2021) used the UAV to collect images of the cracks at the bottom and the side of the main beam, then the image with obvious cracks was located, magnified and cut, and the two-dimensional spectrum of the image was estimated. The crack information was enhanced by filtering out the low-frequency information, thus realizing the self-identification of the bridge surface cracks. Abdellatif et al. (2021) used a combination of region-based and pixel-based methods to detect and accurately locate cracks from multiple-scales. This method has been proven to have high noise immunity. Peng et al. (2021) has equipped a UAV system that can simultaneously capture images of bridge cracks and their GPS locations, and then crack identification and measurement of crack width were achieved by mixing advanced features, shape features, and gray features. In order to further improve the efficiency and accuracy of bridge crack identification through digital image processing methods, Yu et al. (2023) proposed an intelligent bridge crack detection method integrating YOLOv5 and U-Net3+ algorithms. In this method, the YOLOv5 target detection algorithm was used to realize the rapid identification and location of bridge cracks. Based on the U-Net3+ crack segmentation algorithm, an eight-direction crack width measurement method was established to achieve high-precision measurement of crack shape and crack width. Xie et al. (2022) used an underwater robot equipped with a high-definition underwater camera to analyze images with cracks through filter smoothing and edge detection. Based on the Euclidean distance, the crack width was calculated through an iterative algorithm for slope calculation.

### 2.1.2. *Detection of other concrete apparent damage*

The statistical analysis of the apparent damage of concrete, such as voids, hungry spots, spalling and edge failure, is an important content of concrete bridge detection and analysis. For the surface damage at the bottom and side of the beam that is inconvenient to observe, the detection and classification of them can be realized by means of proximity detection with the help of machine equipment and graphic processing technology. Xie et al. (2018) developed a robot detection system based on vehicle to detect concrete surfaces. The

**Fig. 4 – A steel bridge detection robot and its several practical application scenarios (Nguyen and La, 2021).**

system used a set of high-resolution industrial cameras to automatically capture a large number of images, through the fusion point and line characteristics of the image stitching, thus achieving the concrete surface defect detection. There are various types of concrete apparent damage, and it is very important to accurately classify the damage according to the detected information. To classify concrete damage more intelligently and scientifically, Hüthwohl et al. (2019) proposed a triphasic concrete damage classifier based on deep learning neural networks. The classifier can accurately classify a variety of defect types, and it has achieved more economical and objective detection of concrete damage. Bolourian and Hammad (2020) proposed a three-dimensional path planning method by combining radar and UAV equipment. This method can consider concrete surface damage as factors in potential displacement, which can minimize the flight time of UAVs for the accurate and efficient collection of concrete damage information. Perry et al. (2020) proposed a simplified bridge appearance damage detection system, as shown in Fig. 3. In this system, a UAV carrying vision sensors is used to collect data. Then, use the collected pictures and video information to generate a 3D point cloud and photo-realistic model based on the structure-from-motion model, which is the basis of a geo-referenced as-built bridge information model (AB-BrIM). The human-in-the-loop machine learning technique is employed to create an element-wise model by segmenting each bridge element from the point-cloud. Next, image processing techniques are used to identify structural damage. At the same time, the damage information is mapped to the AB-BrIM to achieve quantitative, accurate and efficient assessment of the apparent damage of bridge structures.

### 2.2. *Intelligent detection of steel structure apparent damage*

The apparent disease characteristics of steel structures are different from those of concrete structures, and the main manifestations are corrosion, coating spallation, weld cracking, and fatigue cracks. Aiming at figuring out the characteristics of surface damage of steel structures, Potenza et al. (2020) developed a program for structural surface damage recognition based on image color information, and the image information was obtained by UAVs. This program can automatically identify the coating spallation, corrosion and other damage on the surface of the steel structure. Kim et al. (2020) proposed an intelligent image analysis method that can account for different colors and uneven illumination. The method realized the monitoring of steel structure surface corrosion. Dong et al. (2020) proposed a parallel structured light (PSL) sensing method based on deep learning and information fusion to detect weld lines. This method utilized a camera to capture the laser stripe image projected by the PSL on the weld, and then, trained a MobileNet-SSD deep learning model to extract the region of interest to remove the noise of the laser stripe image. Finally, the weld line was obtained by fusing the information of multiple weld boundaries. In order to effectively improve the detection efficiency of fatigue cracks in orthotropic steel bridge decks, Han et al. (2021) designed an intelligent detection robot that combined image processing technology and ultrasonic phased array detection technology. The robot moved on the surface of the U-rib structure by means of electromagnetic adsorption. Combining visual images and thermal imaging image information, Lim et al. (2021) used the regional convolutional neural network (RCNN) to automatically detect and classify the surface and subsurface corrosion of steel bridges. Nguyen and La (2021) developed a steel bridge detection robot that integrated various sensors such as hall-effects, IR, inertia measurement units, and cameras. Using these sensors comprehensively, the robot can effectively detect the corrosion and fatigue cracks of steel structures. At the same time, the robot has a good crawling ability. It can independently realize the transition from the plane to a curved surface and has a good ability to cross obstacles, as shown in Fig. 4, which greatly improves the detection efficiency of steel structure surface damage.

### 2.3. *Detection of key vulnerable components of bridges*

Key vulnerable components such as bearings and stay cables play an important role in the safety of bridge structures, and it is necessary to have a timely grasp and understanding for their situation. As the main force-transmitting component of the bridge, the bearing is located in a narrow space. So, there are many difficulties in manually detecting the bearing. When the robot is used to detect the bearing, due to the occlusion of the line of sight, there are certain difficulties in the remote control of the robot, which requires that the bearing detection robot can independently realize the effective detection of the bearing. For this reason, Peel et al. (2018) proposed a scheme of robot for bridge bearing detection. The scheme realized the localization of the robot through the adaptive Monte Carlo localization method and improved the autonomy of the robot by using the docking station. Ikeda et al. (2019) added a multi-degree-of-freedom robotic arm to the UAV and installed a camera on it, so effective observation of the bearing can be achieved. Stay cable is the most important bearing member of the cable-stayed bridge, and its safety has been widely concerned. Wang et al. (2021) proposed a wirelessly controlled stay cable detection robot and analyzed the effects of stay cable diameter, inclination and cable force on the robot's crawling. To strengthen the spanning ability of the cable detection robot, Li et al. (2022) proposed one type of the robot with a new elastic suspension system and an axial rotator. The robot can successfully cross obstacles such as cable clamps to achieve automatic detection of cables. Bolt-connected fabricated components are prone to loosening of bolts under the repeated action of various loads such as vehicles and temperatures. Therefore, it is very important to ensure the safe operation of the bolt. Huynh et al. (2019) proposed a method for bolt looseness detection fused with deep learning. The method realized the detection of bolts through the RCNN, estimated the angle of the bolts from the bolt image through the image processing algorithm based on the hough line transform, and then judged whether the bolts are loose. Ju et al. (2022) proposed an algorithm based on the self-attention mechanism and center point regression model to realize bolt detection. In this method, the target was directly predicted as a point, and the bolt center point heat map construction method was used to accurately predict the target size of the bolt area. At the same time, the self-attention semantic segmentation algorithm was adopted to focus on the target bolt area and suppressed the background area, thereby effectively improving the detection performance.

## 3. Intelligent monitoring equipment and technology

To quickly monitor the status of bridges, many important bridges are equipped with bridge health monitoring systems. The main function of the bridge health monitoring system is to sense the load environment of the bridge (vehicles, temperature, etc.) and monitor the response (strain, deflection, acceleration, etc.) of the bridge under operational loads, so as to realize the early warning of the abnormal condition of the bridge. The complexity of the actual operating environment of bridges and the lack of accuracy and robustness of traditional sensors make the reliability and stability of traditional health monitoring systems still need to be improved. In recent years, many scholars have tried to use more intelligent devices as well as advanced techniques for bridge structural response measurements.

### 3.1. *Intelligent monitoring of structural quasi-static displacement*

The quasi-static displacement of the bridge structure may change the stress characteristics of the structure and affect the safety of the structure. Many scholars have tried to use advanced equipment, such as UAVs and radars, to measure the quasi-static displacement of structures. Reagan et al. (2017) used a combination of UAVs and 3D digital image correlation to perform long-term monitoring of bridge quasi-static displacement based on non-contact, optical measurements. The method has been applied to the quasi-static displacement monitoring of two concrete bridges, and the results show that the method can realize the measurement of the geometric shape change of the structure with high precision. Yoon et al. (2018) proposed a method for bridge quasi-static displacement monitoring using UAVs. This method used a target-free method to extract the relative structural quasi-static displacement from the video, uses the background feature points to calculate the absolute motion information of the camera mounted on the UAV, and combines the above information to realize the measurement of the absolute displacement of the structure. Lee et al. (2019) used the LiDAR system to monitor the long-term displacement of small and medium-span bridges. This method didn't require permanent installation of the LiDAR system. Ribeiro et al. (2021) proposed a method for measuring plane quasi-static displacement of structures based on a combination of the UAV and image processing. This method evaluated the relative displacement between the structure and the UAV based on target tracking and introduced an embedded inertial measuring unit through the UAV to remove the influence of UAV motion on the measurement. The accuracy and validity of the method were proved by the field test.

### 3.2. *Intelligent monitoring of structural dynamic response*

The measurement of structural dynamic response requires high stability accuracy and sampling frequency of the measurement equipment. The traditional modal identification method is a modal analysis by vibration information at a fixed position, which has a low spatial resolution. To improve the spatial resolution of the vibration information recognition, Marulanda et al. (2017) developed a device that can identify dense mode shapes. Through experimental verification, the device can successfully identify dense vibration mode with a small number of sensors. Lynch et al. (2016) proposed a device that can not only measure the dynamic response of structures, but also perform impact load testing. The device used a UAV as a platform, and integrated robotic grippers and wireless sensors on the UAV. The robotic gripper can grasp and place heavy objects for impact load testing. The wireless sensor can collect the vibration response information of the structure under the impact load, and then carry out the modal analysis of the structure. Shao et al. (2020) proposed a holographic visual sensor and develop the corresponding algorithms for the measurement of structural vibration. In this method, an automatic camera

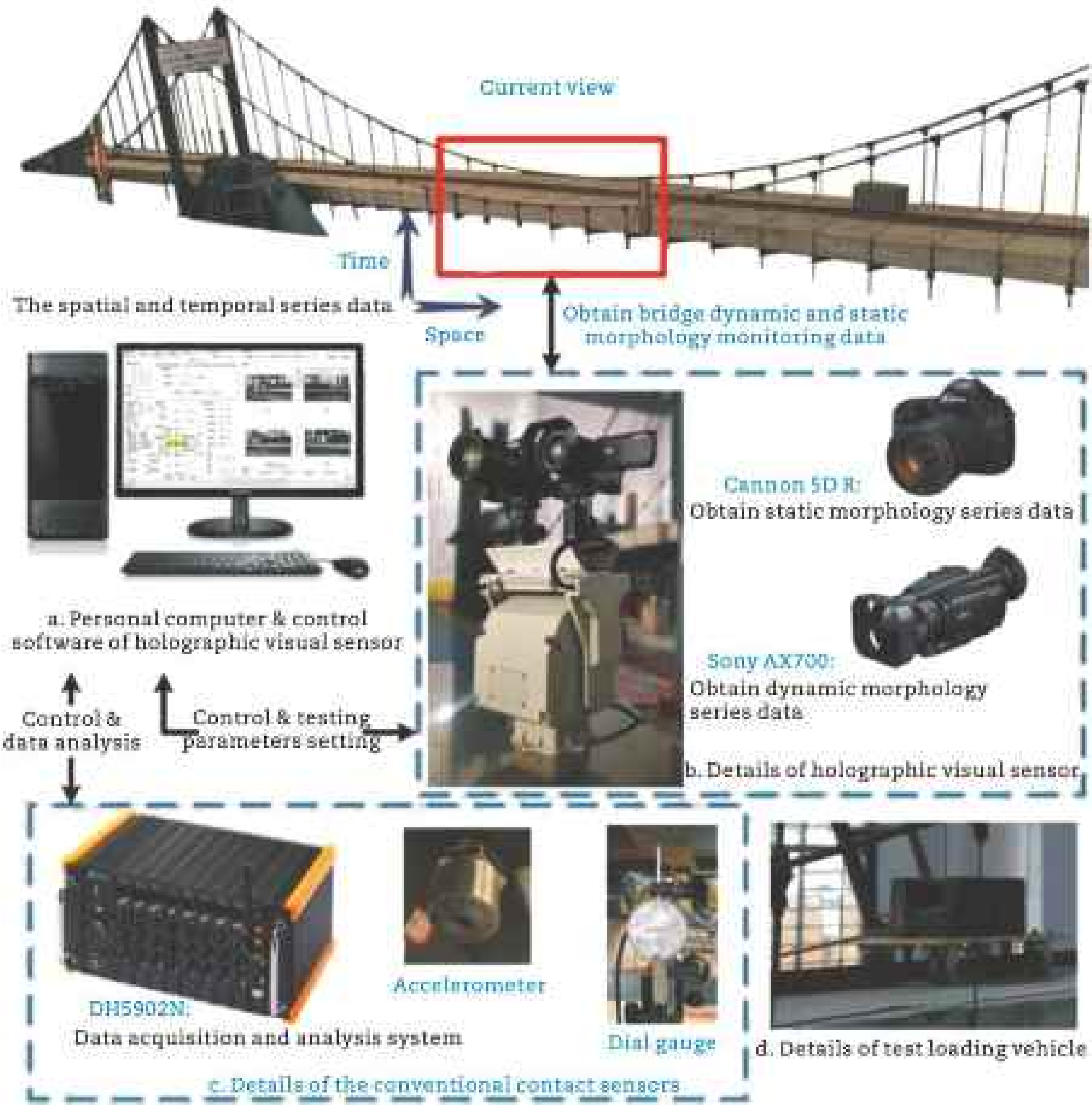


**Fig. 5 – A full-field non-contact structural geometry morphology to measure the dynamic response of a structure (Shao et al., 2020).**

patrol experimental device is employed to collect the bridge's video under various damage/activities. At the same time, the holographic geometric morphology tracking algorithm was introduced based on the temporal and spatial characteristics of the series data. The usage scenario of this method is shown in Fig. 5. The personal computer and control software of holographic visual sensor were used to analyze and collect the data collected by the sensor. The holographic vision sensor can arrange dense and continuous pixel-level/sub-pixel-level virtual measurement points on the spatial surface of the measured object; therefore, the actual physical characteristics of the structural geometry and deformation can be obtained. Experimental results show that the method can accurately measure the full-field displacement and dynamic response of the structure under different conditions. Similarly, the dynamic response of structures is extracted based on visual information. Chen et al. (2021) proposed a bridge vibration test method combining the UAV and digital image correlation. In this method, the bridge model was photographed by a UAV, and the dynamic displacement of the measurement point was tracked by means of digital image association, and then the dynamic displacement time history of the measurement point was obtained. Zhao et al. (2019) combined support correlation filters algorithm with KanadeLucas-Tomasi algorithm to identify bridge dynamic displacement through video. This method has shown to be more accurate and robust than the support correlation filters algorithm alone and the KanadeLucas-Tomasi algorithm alone. Perry and Guo (2021a, b) carried an optical camera and an infrared

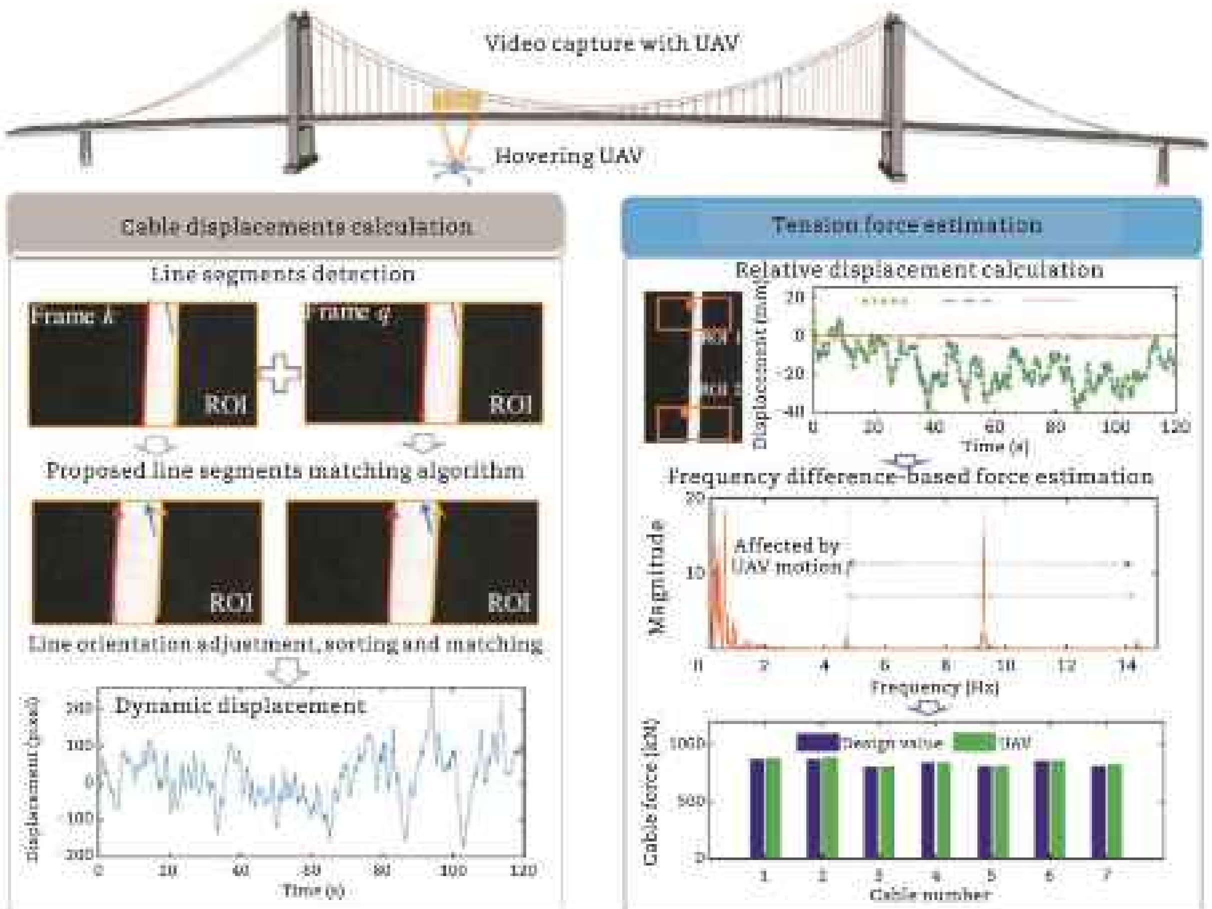


**Fig. 6 – Basic concept of the method for UAV-enabled cable force estimation (Tian et al., 2021).**

camera pair on the UAV platform to measure the dynamic structural response, and developed a data post-processing algorithm to extract the dynamic displacement of the three-dimensional structure in three degrees of freedom.

Using the vibration information of the cable, the evaluation of the cable force can be realized. The traditional method of measuring cable force mainly uses an accelerometer or electromagnetic sensor. In order to measure the cable force more conveniently, scholars tried to use various non-contact measurement methods. Tian et al. (2021) installed a camera on the UAV to capture the vibration image of the cable, and used a line segments detector to identify the edge of the cable. On this basis, the dynamic displacement of the cable can be measured, and thus the vibration frequency of the cable can be identified. Finally, the cable force was calculated by determining the frequency difference of adjacent high-order frequencies. The basic concept of the overall approach is shown in Fig. 6.

## 4. Intelligent data analysis

The prolonged operation of bridge health monitoring systems will result in the accumulation of a significant volume of data. The data quality of the bridge health monitoring system is critical to the condition evaluation of structures as well as the reliability of safety warnings. In reality, missing, drift, outlier, trend, noise, and other anomalies can result from sensor failures, communication errors, and other reasons. Therefore, it is necessary to detect the abnormal data of the bridge health system and deal with the abnormal data in time. In the traditional health monitoring system, abnormal data is not effectively processed, resulting in poor overall data quality. In recent years, artificial intelligence algorithms have developed rapidly and are widely used by scholars because of their powerful generalization ability. Many scholars have built neural networks to analyze the data collected by the bridge health monitoring system intelligently. Bao et al. (2018) converted the time series data collected by the health monitoring system into a vector and plotted this vector in a grayscale image, mined the image information through deep learning, and used the image information features of the data to identify abnormal data. There are several ways to convert time series data into images. Tang et al. (2019) visualized the original time series data in time domain and frequency domain respectively to form a two-channel image. Then, the features of the image were marked. The image features can be extracted by training the CNN model, and then the identification of abnormal data was realized. The basic process is shown in Fig. 7. Mao et al. (2020b) combined the generated confrontation network with the automatic encoder, converted time series data into Gramian

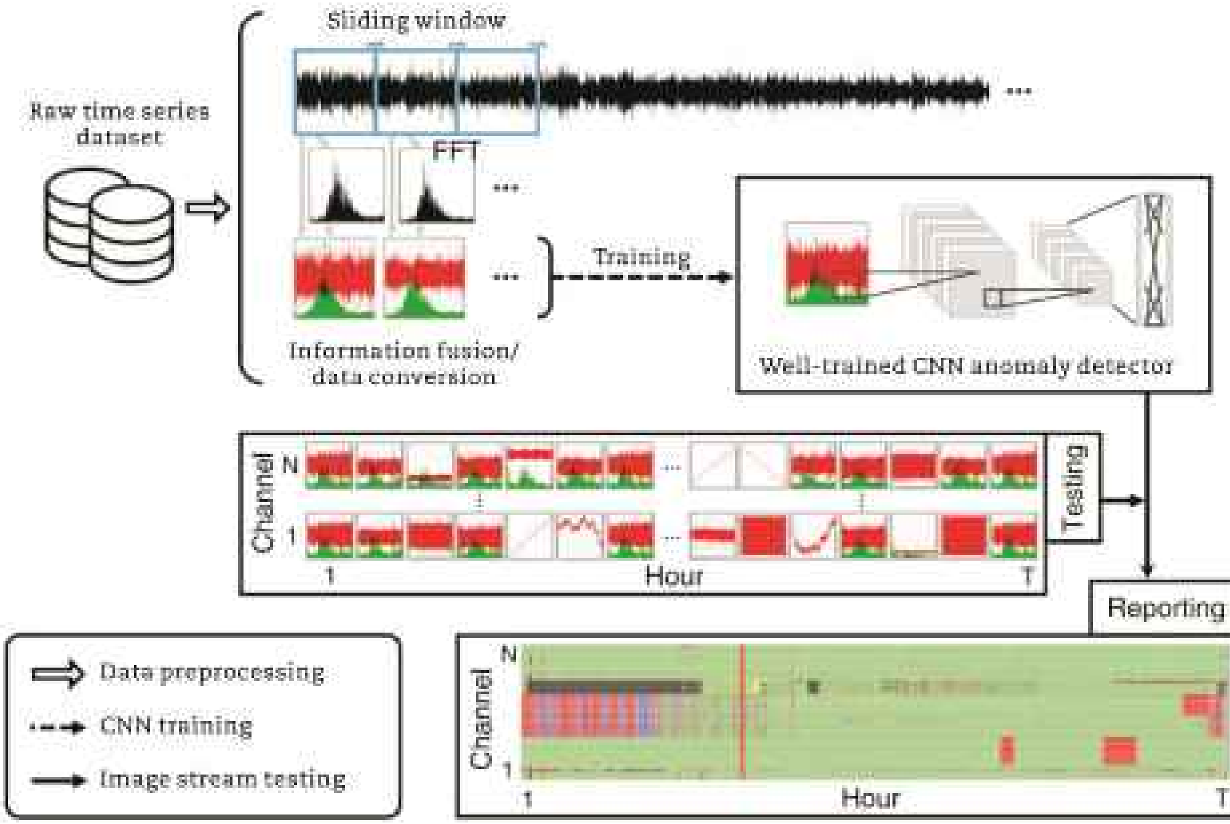


**Fig. 7 – Workflow of the anomaly data detection method (Tang et al., 2019).**

angular field images, and integrated advanced computer vision algorithms into the network. Then, the detection of abnormal data was realized.

While identifying abnormal data, how to recover lost and damaged data has been widely concerned by scholars. Ni et al. (2019) used a one-dimensional CNN to directly extract data features from the input signal to judge the abnormality of the data. At the same time, a data compression method based on an auto-encoder was developed to achieve data compression and reconstruction. The basic process is shown in Fig. 8. Xu et al. (2020) processed data based on wavelet transform and generalized Pareto distribution and combined the two indicators of data anomaly threshold and anomaly trend to judge whether the data was abnormal. The detection of the trend was discussed using the moving fast Fourier transform.

For the recovery of missing data, it can be regarded as different problems from different angles, such as the prediction problem of time series data, the conditional probability modeling problem, and so on. Li et al. (2020) transformed the data recovery problem into the prediction problem of time series data, decomposed and model the data through empirical mode decomposition, predicted the time series data through the long short-term memory model (LSTM), and then realized the recovery of lost data. Lei et al. (2020) proposed a deep convolutional generative adversarial network to achieve data recovery. In this method, a generator was used to extract the features of the data, a discriminator was used to identify the result of data recovery, and the identification result was fed back to the generator. After continuous training and adjustment, a robust data recovery model was formed to realize data recovery. Tang et al. (2020) regarded the recovery of missing or abnormal data as an optimization problem of matrix recovery and regarded the data recovery problem based on compressive sensing as a regression problem. The method intelligently restored data based on the CNN. Yang et al. (2021) used the bi-directional LSTM model to classify, judge, and locate the missing, outliers, drifts, and trends of the data. Jiang et al. (2022) regarded data recovery as a conditional probability modeling problem and proposed a novel data recovery method based on deep learning. This method used a deep fully CNN with an encoder-decoder structure to capture the overall semantic features of bridge monitoring data and utilized a novel perceptual loss function to achieve data integration under different data loss modes.

## 5. Intelligent evaluation and early warning

The traditional bridge assessment methods are not time-sensitive, and timely and effective bridge status assessment and early warning are very important for the long-term operation of bridges. Based on scientifically exploiting and analyzing the characteristics of data from bridge detection and monitoring, the evaluation and prediction model to reflect the state of the bridge structure can be established by

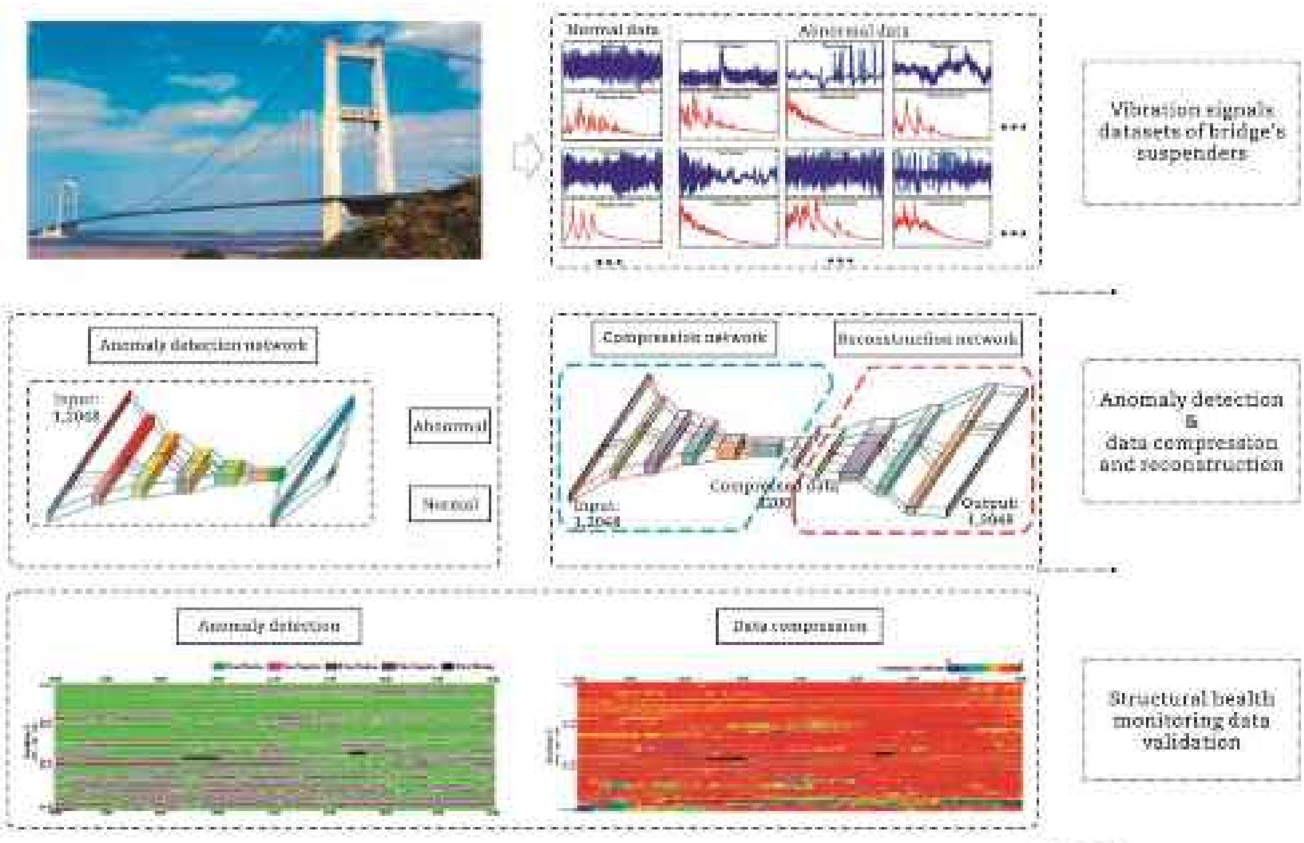


**Fig. 8 – Workflow of the anomaly detection, data compression and reconstruction method (Ni et al., 2019).**

intelligent algorithms, so as to realize the intelligent evaluation and early warning of the bridge structure, which is also a research hotspot of scholars. It is very important for the operation and maintenance management of the bridge to give more accurate and efficient early warning of abnormal conditions. Li et al. (2017) proposed a rapid vortex-induced vibrations (VIVs) identification method based on unsupervised learning through cluster analysis of a large amount of wind and wind-induced vibration data to enable early warning of VIV events on large-span bridges. Li et al. (2018a) collected six years of field-measured VIVs from large-span bridges and established a VIVs database. Using the database, a VIV identification model was established through the decision tree learning algorithm and the support vector machine regression model. The proposed method can accurately identify and predict the VIVs from various modes. Zhao et al. (2020) trained a deep learning regression network based on a LSTM for non-linear mapping between multiple sources of monitoring data to achieve a rapid evaluation of the in-service condition of bridge structures. Zhang et al. (2021) proposed a probabilistic Bayesian optimization framework for typhoon dynamic response prediction of large-span bridges, based on Bayesian optimized quantile random forest, for real-time prediction from a data-driven perspective.

The traditional calculation theory and method are used to calculate and evaluate the performance of the bridge, which is usually based on certain assumptions and different from the actual structure state. In recent years, some scholars have built models to reflect the performance of structures based on the data-driven approach. Feng and Wu (2022) proposed a machine learning-based method for predicting the basic performance of concrete structures, which can directly give the performance index of concrete structures based on the basic design parameters of the structures (such as geometry, material properties, load conditions, etc.), and thus evaluate the performance of concrete structures. Zhao et al. (2022a) proposed a digital method of distributional mapping from the structural temperature field to the temperature-induced strain field. The mapping relation was established based on the learning of the big data of distributional feature parameters by the bidirectional long short-term memory regression network. It is common to use high-fidelity data to analyze bridge structures. In reality, however, it is difficult to obtain large amounts of high-fidelity data directly. Chen and Feng (2022) proposed a framework for data analysis using low-fidelity data combined with a small amount of high-fidelity data, as shown in Fig. 9. The accuracy of the method was also verified using an example of reinforced concrete deep beam shear-bearing capacity analysis. Li et al. (2018b) utilized the monitoring data of the inclined cable force to conduct the intelligent evaluation of the state of inclined cables, combined with the Gaussian Mixture Model and Bayesian Information Criterion. Ni et al. (2020) conducted a probabilistic analysis of the regression pattern between

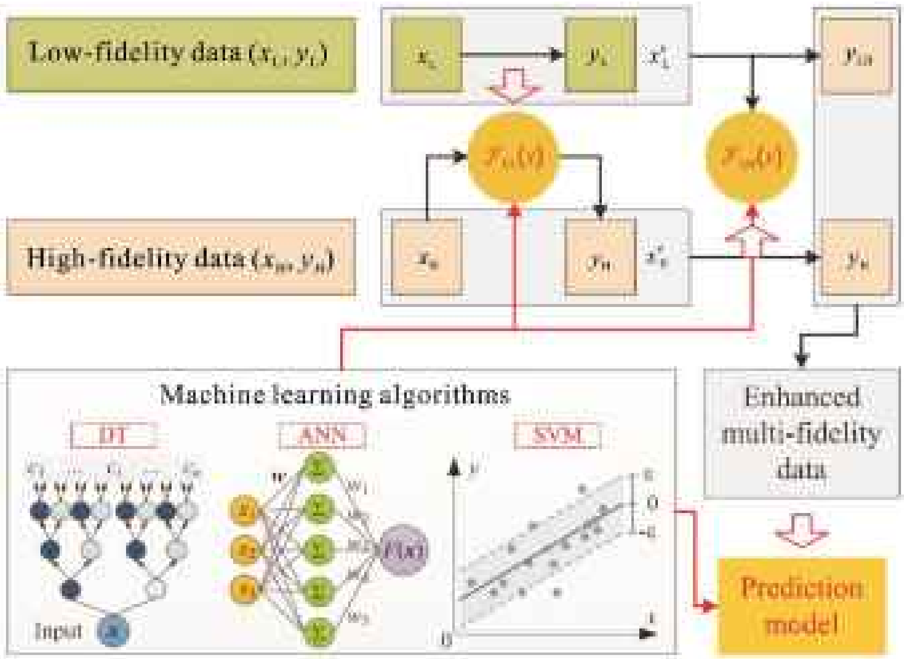


Fig. 9 – Multifidelity enhancement framework based on machine learning algorithms (Chen and Feng, 2022).

expansion joint displacement and ambient temperature of large-span bridges based on Bayesian methods using health monitoring data. Meanwhile, an index to measure the abnormal state of expansion joints was proposed in conjunction with reliability theory, which in turn enables the evaluation and early warning of expansion joint performance. Wu et al. (2020) proposed a modal corner superposition method to estimate the cumulative displacement of bridge beam segments. The method integrated the bridge end turning angles and the modal parameters of the bridge. Based on this, the life of bridge bearings was predicted. Algorithms can also be used to link phenomena to knowledge. Zhao et al. (2022b) proposed a paradigm of the digital state-monitoring of abnormal vibration of cables based on the identified modal parameters of non-stationary sections. In this method, an automatic extraction of the non-stationary section of abnormal vibration was conducted. Based on this, a new process of modal parameter identification was proposed.

Bridges play an important role in road transport networks. However, due to harsh environments, overloading, initial structural damage, and other factors, the structural deterioration and damage of road bridges are a growing concern. It is a major challenge to quickly assess the condition of bridges at the network level and to efficiently ensure the safety of bridges at the regional level. For this reason, Xia et al. (2021) integrated long-term bridge detection data from network-level bridges, developed a deterioration model for regional bridges, and proposed a data-driven network-level bridge condition assessment framework.

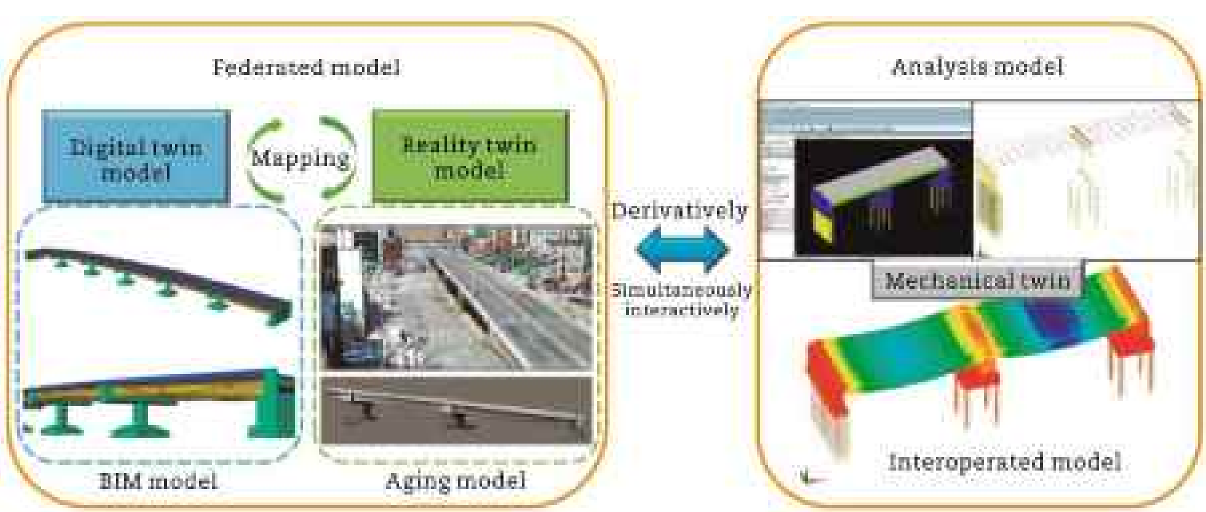


Fig. 10 – Digital twin model concept for bridge maintenance (Shim et al., 2019).

## 6. Intelligent repair and maintenance

As the scale of bridges continues to grow and their service life increases, their operation and maintenance management is becoming more and more important. The planning of traditional bridge operation and maintenance services is mostly based on manual experience. This can lead to over-maintenance or missed optimal maintenance times. It is necessary to plan and manage the whole life cycle of bridges, determine the timing of maintenance scientifically, and develop maintenance strategies in a reasonable and economical manner. Shim et al. (2019) proposed a bridge maintenance system that enables more reliable decision-making by using the concept of a digital twin model, as shown in Fig. 10. The system combined the management and maintenance system based on a 3D information model and the bridge detection system. The formulation of maintenance strategies needs to comprehensively consider various factors such as time cost, capital cost, and labor, which is a complicated process. It is possible to efficiently handle complex mapping problems with the help of neural networks. Wei et al. (2020) proposed an automated deep reinforcement learning framework to intelligently obtain an optimized structural maintenance policy. In this framework, there are two roles, the decision maker and the structure to be maintained. The decision maker was used to determine the maintenance strategy, and the repaired structure gave feedback to the decision maker under specific maintenance actions. Mao et al. (2020a) treated the optimal maintenance scheduling problem as a two-layer programming problem consisting of a multi-objective nonlinear programming model and a modified user equilibrium model. Subsequently, the model was equivalently transformed into a single-layer model and solved by the simulated annealing algorithm. The maintenance of network level bridges requires accurate and efficient identification of the bridges that are most in need of repair. Therefore, it requires a network-level bridge vulnerability analysis. Wang et al. (2020) used an improved ORDER-II-Dijkstra algorithm based on Bayesian networks to analyze the vulnerability of network level bridges. To reduce the cost of bridge rehabilitation to a greater extent, Nili et al. (2021) proposed a simulation-based bridge maintenance optimization method by using the genetic algorithm and discrete event simulation.

## 7. Conclusions and prospects

Intelligent operation and maintenance of bridges have become an interdisciplinary research field combining multi-disciplinary theories, methods, and technologies, and its research methods and practical applications have been greatly developed. This paper sorts out the development in recent years from the aspects of intelligent detection equipment and technology, intelligent monitoring equipment and technology, intelligent data analysis, intelligent evaluation and early warning, and intelligent repair and maintenance. The conclusions are as follows.

(1) In the field of bridge detection, intelligent equipment such as UAVs, mobile robots, circular climbing robots, and multi-functional detection robots have emerged to achieve high-efficiency and full-coverage observation of bridge components. At the same time, advanced technologies and algorithms such as computer vision, ultrasound, and machine learning were used to accurate classification and analysis of bridge apparent damage. Compared with the traditional detection method, the intelligent detection method guarantees the safety of the detection personnel and greatly improves the efficiency and accuracy of detection.

(2) More accurate and stable bridge response measurement methods have been proposed. Advanced devices such as UAVs and robots were used to carry the measuring instruments. At the same time, the methods such as photogrammetry, laser, and electronic waves were used to achieve more accurate and stable measurement of the bridge response.

(3) Many intelligent algorithms have been proposed to realize the analysis and processing of massive data. For abnormal data detection methods, it can be divided into the following two categories: one is to convert time series data into images and use a deep learning algorithm to indirectly judge the abnormality of data; the other is to extract data features from time-series data through algorithms, and directly judge the abnormality of the data. For the recovery of abnormal data, scholars mainly used a large amount of data to train and improve the network on the basis of network structures such as the LSTM and the generative confrontation network.

(4) Different from traditional methods, scholars tried to establish the bridge evaluation and early warning model in a data-driven manner based on a large amount of bridge detection and monitoring historical data. The optimal repair times and structural repair strategies were determined by integrating multi-source heterogeneous data and applying intelligent algorithms. Compared with traditional methods, these methods avoid excessive dependence on human experience. The evaluation and decision-making process is more scientific, which in turn contributes to the cost reduction and efficiency increase of bridge operation and maintenance.

In summary, significant progress has been made in the field of intelligent operation and maintenance of bridges. Further research can be conducted in the following areas. (1) Developing comprehensive intelligent detection equipment suitable for complex environments, and based on knowledge graph models to efficiently and intelligently provide targeted repair recommendations for different types of bridge damage. (2) Researching intelligent fusion and analysis methods for multi-source heterogeneous data, effectively integrating bridge inspection, monitoring, and other heterogeneous data. Based on big data technology, a more accurate digital model of the bridge can be established, providing a basic bridge model for intelligent operation and maintenance of the bridge. (3) Based on the load environment and structural characteristics of the bridge structure, and using intelligent algorithms to study the time-varying evolution laws of the full life performance of the bridge structure under multiple factor effects, to help promote the long-term operation of bridge structures.

## Conflict of interest

The authors do not have any conflict of interest with other entities or researchers.

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**Dr. Wanshui Han** is a professor and the deputy dean of School of Highway, Chang'an University. He was also a visiting scholar of Louisiana State University, USA, and a winner of Shanghai excellent doctoral dissertation. He presided over and participated in several projects including National Key Research and Development Program and National Natural Science Foundation of China. He and his team independently developed the bridge dynamic analysis software-bridge dynamic analysis system (BDANS). He has conducted long-term research in the field of intelligent bridge maintenance and operation.

**Gan Yang** is a lecturer at Chang'an University. He has participated in several projects including National Key Research and Development Program and National Natural Science Foundation of China. He mainly engaged in research on bridge simulation computing and intelligent operation and maintenance of bridges under normal operational loads.

**Dr. Shizhi Chen** is an associate professor at Chang'an University and a visiting scholar at the University of California, Los Angeles. He engaged in research on bridge safety monitoring intelligent evaluation. He presided over and participated in several projects including National Key Research and Development Program and National Natural Science Foundation of China.

**Kai Zhou** is a PhD candidate studying at Chang'an University. He has participated in several projects, including the National Key Research and Development Program and the National Natural Science Foundation of China. He mainly engaged in research on bridge simulation computing and intelligent operation and maintenance of bridges under extreme wind conditions.

**Xin Xu** is a PhD candidate studying at Chang'an University. He has participated in several projects, including National Key Research and Development Program and the National Natural Science Foundation of China. He mainly engaged in research on the simulation of wave loads and intelligent operation and maintenance of bridges under wave loading conditions.