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REVIEW

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Review of anomaly detection in large span bridges: available methods, recent advancements and future trends

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Abstract

During the life-cycle service of the constructed large span bridges, they face various threats every day due to the sophisticated operational environments. To ensure the structural safety, it is necessary to detect potential anomaly. Based on different inspection, monitoring and analysis technique, huge amounts of data that direct or indirect reflect structural characteristics can be obtained, and hence the anomaly detection methods developed. In order to provide a summary of relevant information needed by researchers to realize what is concerned about and how current practices deal with these issues, then further promote the application, this paper reviews understanding of anomaly detection in large span bridges. It starts with an analysis of concerned parameters, including dynamic and static structural parameters of a bridge. The various data sources are then commented. Next, existing anomaly detection methods are reviewed and classified. Finally, this paper concisely provides recent progress and discusses future research trends based on the identified knowledge gaps. We hope that this review will help development in this field.

Keywords: Anomaly detection, Large span bridge, Time series, Structural health monitoring, Intelligent algorithm

1 Introduction

The large span bridges are important parts of infrastructure, which usually locate in critical positions of transportation network such as river, channel, and canyon (Liu et al. 2016; Mehrabi 2016). The large span bridges can provide a solid support for the country's economic and social development, they also present an important manifestation of a country's industrial and technological level (Huang et al. 2020a, b). However, deterioration accumulation and sudden events are inevitable during the life-cycle service of these bridges subjected to harsh service environments (Sun et al. 2020; Fan et al. 2022). The failure of large span bridges will result in considerable losses of both human life and property. During past 20 years, the collapse of more than 120 bridges worldwide has caused major economic losses and casualties (Wang et al. 2022a, b), several typical accidents of large span bridges are shown in Fig. 1. For instance, the I-35W bridge cross

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(a) I-35W Bridge (b) Polcevera Bridge

(c) Nan Fang Ao Bridge (d) Kukar Bridge

Fig. 1 Accidents of large span bridges

Mississippi river in the U.S. collapsed during peak traffic hours on August 1, 2007 due to severe corrosion induced fracture of steel components, and resulted in 13 deaths and 145 injuries (Hao 2010). The pioneering cable stayed bridge over the Polcevera in Italy failured suddenly on August 14, 2018, which left 43 people dead. The accident began with breaking of the cable close to the antenna (Invernizzi et al. 2022). Other anomalies can also influence the normal operation of a large span bridge, such as cable damage, excessive deformation, structural vibration, or stress redistribution.

Monitoring the large span bridge condition and detecting their anomalies are important to ensure serviceability and safety of bridges. Most serious accidents can be avoided by intervening in the early stage of damage accumulation. Anomaly detection of bridges help detect potential issues before they become severe and eventually lead to structural failures. It can prevent potential accidents by identifying covert problems and then maintain in a timely manner. To the perspective of economy, detect bridge anomalies early can save costs of more extensive repairs or replacements (Liu et al. 2020; Fan et al. 2022). In order to achieve anomaly detection of large span bridges, bridge management department usually inspect the whole bridge regularly based on prescriptive code to find structural diseases, mainly some apparent defects such as cracking, corrosion, component deformation, etc. However, these periodic inspections have proven to be ineffective for anomaly detection, as damage may appear after an inspection and not be detected until next one, leading to further deterioration of the bridge and increased cost of its eventual repair or replacement, if not to its collapse (Rios et al. 2023). Combine the inspection results with other ways, including the finite element (FM) analysis, the structural condition of a bridge can be evaluated. Meanwhile, more hidden problems can not be detected by visual inspection. Due to the rapid increase of the number of large span bridges, it is hard to continuously inspect and evaluate the structural condition of each bridge by visual inspection. With the development of computer and sensing technology, structural health monitoring (SHM) system has gained widely attention from the engineering communities and been installed in many large span bridges to constantly collecting the real time data that can reflect the condition of bridges (Doebling et al. 1998; Aktan et al. 2000). Hence, many SHM data driven anomaly detection methods were proposed. The simplest anomaly detection method using SHM data is to set a static threshold (Zhang et al. 2022a, b). Once measurements exceed the pre-set static threshold, the monitoring system will raise an alarm and reminder to bridge management department. The static threshold-based method is easily influenced by bridge operational environment, it is needed to separate various components in raw data (Kromanis and Kripakaran 2016). Furthermore, some indirect information contained in SHM data are mined to be anomaly detection indicators. Recently, more anomaly detection methods have been proposed, involving finite element (FE) model, time series analysis, machine learning technique, etc. (Zeng et al. 2019; Lin et al. 2021; Yu et al. 2021; Wang et al. 2023).

In the past decade, through the research and cooperation of scientists and engineers all over the world, many practical anomaly detection methods have been developed and successfully used in large span bridges. Despite intensive publications, little has been done to comprehensively study all the aspects. In order to further promote the application of bridge anomaly detection of large span bridge, this paper is dedicated to summarize current methods and review recent research advances. In addition, future research trends are also addressed based on the identified knowledge gaps.

2 Concerned parameters

The basic premise of most anomaly detection methods is that anomaly will affect dynamic or static parameters of a bridge (Sohn 2007; Adewuyi et al. 2009). During operation period of a structure, measurements that reflect structural condition are recorded and then indicators are extracted. After comparing measured result with the theoretical one, people are able to judge if the features deviate significantly from the normal range. Ideally, an alarm will be raised if indicators increase above the pre-set threshold (Worden et al. 2000). In order to achieve anomaly detection for large span bridges, dynamic or static parameters should be firstly obtained. The usually concerned parameters including vibration parameters, vertical girder deflection, cable force, structural strain, and girder end displacement.

As dynamic parameters, the vibration parameters of a bridge including vibration mode, frequency and damping. These parameters may vary due to structural performance degradation and sudden events, that can be adopted as a direct index for anomaly detection (Comanducci et al. 2016). Theoretically, structural damage will reduce the stiffness and increase the damping, thus decreasing the frequency and change the vibration mode (Pandey et al. 1991). For a structural free vibration equation:

$$[\mathrm{M}]\{\ddot{x}\} + [\mathrm{C}]\{\dot{x}\} + [\mathrm{K}]\{x\} = \{0\} \tag{1}$$

where $[M]$ is the mass matrix, $[C]$ is the damping matrix, $[K]$ is the stiffness matrix. The eigenvalues and eigenvectors can be obtained from the following characteristic equation:

$$\left([\mathrm{K}]-\omega^2[\mathrm{M}]\right)[\phi]=\{0\} \tag{2}$$

where ω is the frequency, $[\phi]$ is the vibration mode matrix. Assumed that when mass matrix and stiffness matrix occur slight change $[\triangle M]$ and $[\triangle K]$, structural frequency and the vibration mode matrix will also change $\triangle\omega^2$ and $[\triangle\phi]$. Hence the Eq. (2) can be expressed as:

$$\left(([\mathrm{K}]+[\Delta\mathrm{K}])-\left(\omega^2+\Delta\omega^2\right)([\mathrm{M}]+[\Delta\mathrm{M}])\right)([\phi]+[\Delta\phi])=[0] \tag{3}$$

For a large span bridge, the influence of structural anomaly to its mass can be ignored. The Eq. (3) can be simplified to:

$$\left(([\mathrm{K}]+[\Delta\mathrm{K}])-\left(\omega^2+\Delta\omega^2\right)[\mathrm{M}]\right)([\phi]+[\Delta\phi])=[0] \tag{4}$$

Then, simplify the Eq. (4) and simultaneously ignore the second-order terms in it, change of frequency corresponding to a specific vibration mode ϕ_i is deduced as:

$$\Delta\omega_i^2=\frac{\{\phi_i\}^T[\Delta\mathrm{K}]\{\phi_i\}}{\{\phi_i\}^T[\mathrm{M}]\{\phi_i\}} \tag{5}$$

The Eq. (5) is also defined as frequency damage equation. The location and degree of structural damage can also be reflected by theoretical derivation. In some cases, the local mode of components can also be used as specific indexes to detect anomaly (Wickramasinghe et al. 2020). However, for an actual large span bridge, the damage or other anomaly induced frequency change is negligible, it is difficult to detect it. Meanwhile, like many other measured signals bridge frequencies are significantly affected by complex operational environment such as environmental temperature, wind, and traffic load, resulting in a misunderstanding structural condition (Kullaa 2011; Wang et al. 2022a, b).

In view of the limitations of dynamic parameters, structural static parameters have gradually been adopted as an indicator for anomaly detection of large span bridges. Among these static parameters, vertical deflections of main girder are one of the most essential fingerprints to assess the global behavior of large span bridges (Rodrigues et al. 2011; Brownjohn et al. 2015). When the specific correlation between the operational condition and the girder deflection changes, it is indicated that anomaly may occur and lead to the variation of structural stiffness characteristics (Yang et al. 2018; Xu et al. 2019; Fan et al. 2021). Therefore, girder deflection can be regarded as an effective parameter for anomaly detection and has been widely used in many actual bridges. The large span bridges are usually cable supported bridges, including suspension bridges, cable stayed bridge and some arch bridges. For these bridges, cables are very important components to resist various loads, structural anomaly will affect the characteristics of cables. Meanwhile, cable anomaly may also cause serious consequences for the whole bridge. Cable force is the most direct parameter that reflect service conditions and hence study anomaly detection methodology. In China's evaluation standards of highway bridge (JTG/T H21-2011), cable anomaly can be controlled by monitoring the variation rate of the cable forces for a cable. The variation rate of 10% compare to initial cable force is determined as a reference of if anomaly happen. The AASHTO LRFD Bridge Design Specifications

(AASHTO 2017) also regard cable force as an anomaly index and the 75% limit value of normal condition is set as threshold. In addition, strain data is prospective information to be made full use of, since it reflects the structural stress peak and especially sensitive to local stress redistribution, which is the probably anomaly in the vicinity. When there is anomaly event triggering, significant change of strain or strain-based indicators will appear (Ni et al. 2012; Ren and Zhou 2021). In recent years, the girder end displacement was also adopted as a critical parameter to evaluate large span bridges, especially their restraint devices (e.g., bearings) (Ni et al. 2020).

For the collected data, some people directly used the measured physical parameters as anomaly detection index (Xu et al. 2020a), others developed indirect indexes, such as prediction errors, cointegration residuals, Euclidean distances etc. (Huang et al. 2020a, b; Kromanis and Kripakaran 2021; Han et al. 2022).

3 Basic data for anomaly detection

3.1 The FE analysis data

Establishing a FE model of large span bridge based on existing modelling software has been applied with researches to analyze structural characteristics in various conditions, which can help to study bridge anomaly detection. The widely usage of FE analysis greatly save the cost of calculation and bridge in-site testing. On the basis of the established model in different periods (as shown in Fig. 2), various actions can be applied to it according to relevant specifications or actual situation of the bridge, and then calculate structural responses. When using FE models for bridge maintenance and management during service period, further updating or optimization can be made to simulate the influence of diseases. In addition, the FE analysis data can also be mutually verified with data from other sources.

The effectiveness and accuracy of the FE model have a significant impact on the anomaly detection. To ensure the effectiveness of FE model, it is necessary to modify it with actual service condition (Gravitz 2015), the process of modification is shown in Fig. 3. Specifically, the established initial FE model based on design information should be modified or updated with in-site measurements. By modifying parameters such as structural stiffness, boundary, component weight, the FE analysis results tend to actual responses (including dynamic response and static response), making the FE model reflect the bridge condition more accurately. The process of FE model modification mainly involves parameters selection, construction of objective function, selection of optimization algorithm, and iterative solutions. The modification of FE model infers more realistic structural parameters by make its responses in line with that measured in site, which belongings to the category of inverse problems. On the other hands, complex analysis of large span bridges should also quantify the uncertainties and their propagation effects in the FE modelling (Santos et al. 2022).

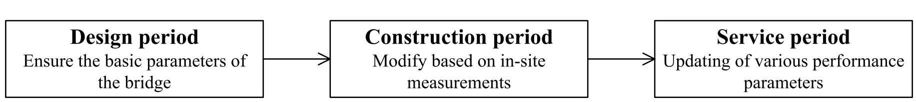

Fig. 2 The FE models of bridge in different periods

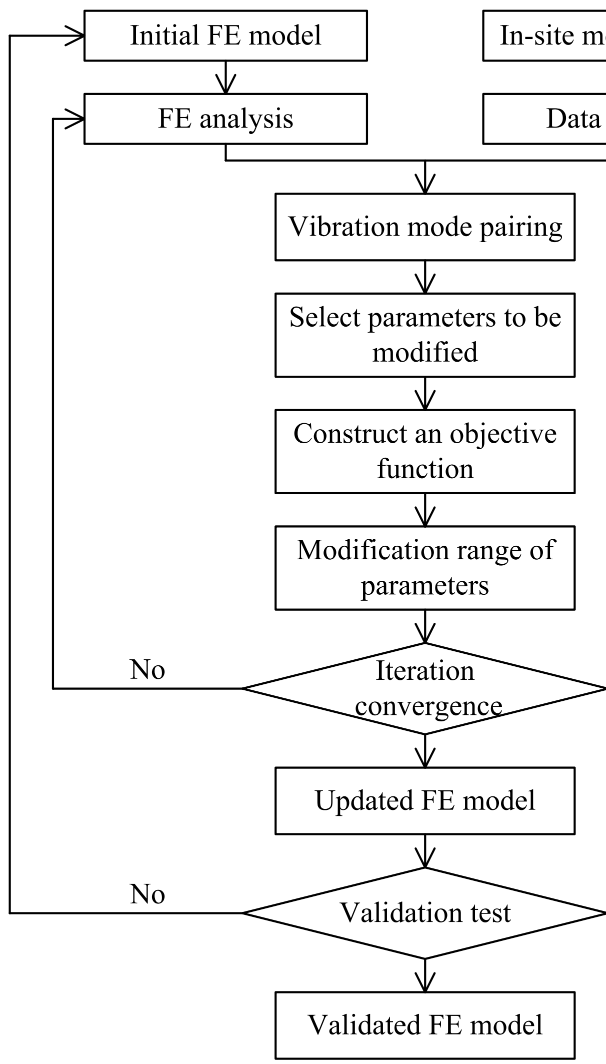

Fig. 3 The flowchart of FE model modification

In many cases, structural anomalies are multi-scale problem, that the damage may involves small crack initiation at the micro-meter scales to the structural damage at large scales (Zhong et al. 2015). Thus, the multi-scale FE model that captures essential behaviors of the structure is useful to successfully detect and track structural anomaly, various studies have been reported on the multi-scale modeling techniques in recent years (Greco et al. 2015). A typical multi-scale FE model of a large span bridge is shown in Fig. 4. In this multi-scale FE model, the orthotropic steel deck was established by solid elements to form a local model. The most vulnerable girder segment at the middle of main span was simulated by shell elements. The global model including cables, towers, piers, girders were simulated by beam or truss elements (Cui et al. 2020). The multi-scale FE models provide a hierarchical description of bridges and makes them easier to be understood. On the macroscale, structural static and dynamic behaviors can be analyzed as a whole, and on the microscale the crack and

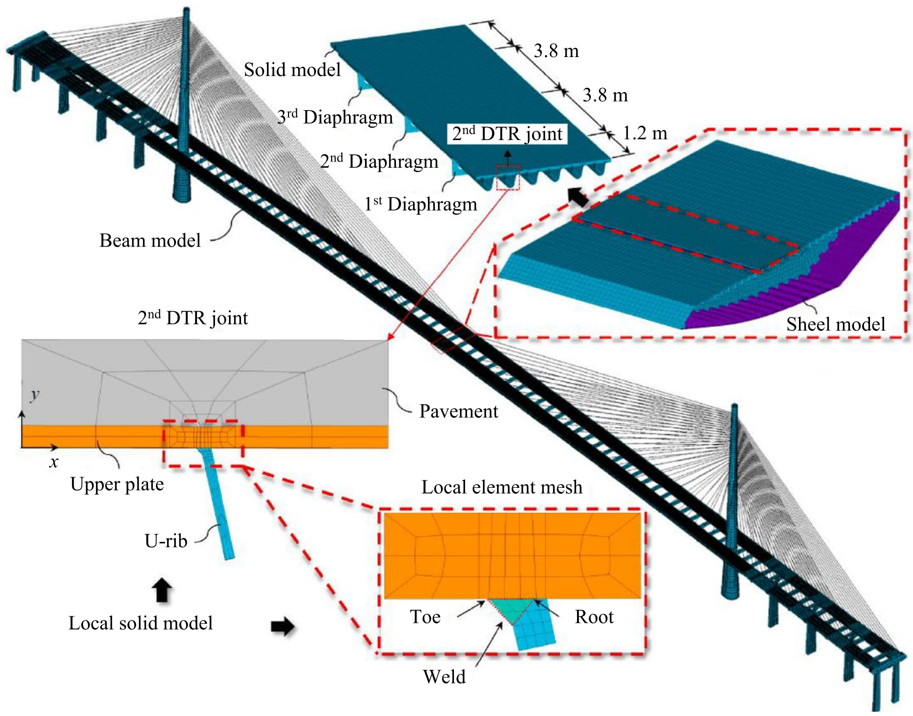

Fig. 4 The typical multi-scale FE model of a cable-stayed bridge (Cui et al. 2020)

damage can be detected at representative locations (Zhong et al. 2016). It has been served as a valuable tool in anomaly detection of large span bridges.

3.2 The SHM data

The SHM technology developed in past decades provides a good solution for the structural data continuous collection. This technology based on a comprehensive sensory system and a sophisticated data processing system and supported by advanced information technology and intelligent algorithms (Xu 2018). One of the most important objectives of SHM is to monitor service conditions, including external environment, load, structural response, then assess its performance and detect if anomaly is present based on monitored dynamic or static characteristics, hence guide the maintenance and management. The SHM framework of large span bridges is shown in Fig. 5.

Data are the pillar of SHM (Makhoul 2022). The large amounts of SHM data need to be managed after collection to support anomaly detection. The data quality plays a crucial role in guaranteeing that the detection is effective. The bridge SHM data are inevitably contaminated due to sensor faults, environmental noise interference, and data transmission failures. Bad data severely disturb the structural anomaly detection. Therefore, it is necessary to clean the raw SHM data before analysis (Pan et al. 2023). The commonly used data cleaning methods including:

- Data transformation: to convert the digital signals collected by various sensors into numerical values that reflect structural characteristics. Usually, there is a linear relationship between output of the sensors and required measurements.

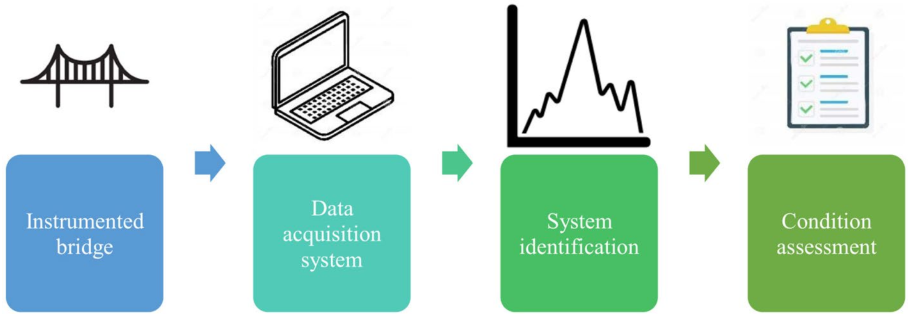

Fig. 5 The SHM framework bridges (Singh et al. 2023)

- Data reduction: to improve the efficiency and reduce space complexity when processing data, this step is prevalent in the SHM anomaly detection (Soleimani-Babakamali et al. 2023). However, the cost is potential information loss.
- Filling the missing data: the interpolation can be used to fill in slight missing data, which can use maximum of current data information as well as maintaining the characteristics. In addition, the missing values can be ignored when it is massive or not important.
- Outlier elimination: use statistical methods to eliminate significant errors, such as Pauta criterion, Grubbs criterion, *t*-test, *F*-test, etc.
- Noise removal: the collected data usually contain noise component, the wavelet method and moving average method can be used for denoising, according to Xu et al. 2020b.

3.3 The inspection results

The SHM systems mentioned before cannot detect all bridge abnormalities due to limitations of measuring points and categories, sensor fault rate may also increase with time. Thus, inspection of bridges during their service life plays an important role in assisting anomaly detection, and facilitating decision-making on maintenance action. Thess activities are conducted rely on visual detection, special equipment, or non-destructive testing (NDT). Different from SHM data, the inspection results usually directly reflect specific defects in a bridge. It is possible to intuitively understand the structural anomalies, thus evaluating the service condition of bridges more accurately. For instance, rather than vibration responses collected by acceleration sensors of the SHM system, the inspection for a cable can obtain its surface and internal defects by equipment (Hou et al. 2020a, b). Generally, inspections are carried out based on prescribed rules, i.e. regular inspections of all bridge components at a determined time interval. This inspection strategy can be referred to as prescriptive inspection (alternatively, time-based or rules-based inspection) (Yang and Frangopol 2022), and is still widely used in many countries. A large span bridge is usually equipped with a bridge management system, see Fig. 6 for instance, where the inspection results can be input to help management.

Besides, many large span bridges will conduct specialized experiments for various components, which can also obtain useful information for anomaly detection.

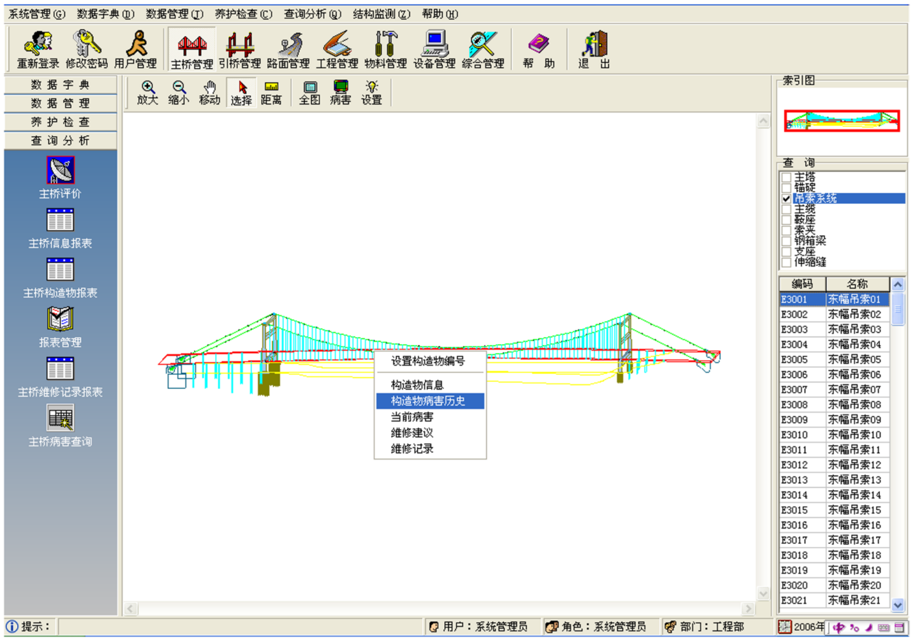

Fig. 6 Instance of bridge management system

4 Categories of anomaly detection methods

4.1 The time series analysis based method

4.1.1 Time series models

Time series methods can be regarded as an output-only and non-model approach, that are popular for anomaly detection of civil structure. Based on the long term monitoring data, time-series models, especially the basic and commonly used auto-regressive (AR) models and moving average (MA) models were widely adopted to extract anomaly sensitive features, for the model coefficients or residuals always contain potential information (Mosavi et al. 2012). The statistical time series model set up a hypothetical mathematical model to describe a time history. Once an appropriate time series model can fit the data, the anomaly from the fitted model can be used to detect structural damage (Brockwell and Davis, 2002). Using the basic AR time series models, Sohn et al. (2000) constructed a two-stage prediction model that combining AR and AR with exogenous inputs techniques to detect the damage of a bridge, model coefficients and the residual error can be defined as the damage-sensitive feature. Carden and Brownjohn (2008) used the ARMA model coefficients to identify different status of a structure. Zheng and Mita (2009) used a pre-whitening filter to remove the correlations in responses, the Itakura distance and cepstral distance computed from AR model were used as detecting indicators. Gul and Catbas (2011) created AR models with exogenous input, and extracted damage features from these models to detect, locate, and estimate the extent of structural changes. Jayawardhana et al. (2015) computed using the AR model coefficient as an effective damage sensitive feature for the detection of structural anomaly. The Fisher information criterion of the computed index is used to statistically decide on the specific location. For these simple time series models, the accuracy of anomaly detection relies much on the continuous regularity of time series data, and they ignore the influence of operational environment. Establish appropriate statistical models and explore effective indicators are essential for anomaly detection.

4.1.2 Fuzzy clustering

In some situations, the appearance of structural anomaly is vague. The switches in damage patterns from one time state to another should be treated in a fuzzy way (Zeng et al. 2019). On the other hands, it is useful to separate the structure related time series data to anomalous status and normal status, which can be descripted as clustering. In the process of clustering, the objects in the same cluster are similar, and the objects between different clusters are distinct. The fuzzy clustering method can be used to handle the time series problem with a fuzzy membership to each cluster. In view of the fuzzy clustering require low computational cost, it have been used to detect structural anomaly based on monitoring data of structures. Silva et al. (2007) selected residual errors that obtained from vibration response measurements as an anomaly sensitive index and then used the fuzzy c-means clustering to quantify it in an unsupervised learning mode.

There have been some successful applications so far (Silva et al. 2007; Zeng et al. 2019).

4.1.3 Cointegration

As a statistical concept in time series analysis, cointegration is widely used to model the long term common trends among economic variables in the field of econometrics. Recently, cointegration has been successfully implemented in the context of massive time series data, where it has been used to remove the confounding influences of operational variations (especially the environmental temperature) that can often mask the signature of structural anomaly (Cross and Worden 2012). The central idea of cointegration is that even if two or more variables are non-stationary, the combination of them will create a new stationary series (Fan et al. 2020). In the definition of cointegration, it is assumed that the input variables series are $\{X_1\}$, $\{X_2\}, ...\{X_k\}$, the corresponding response variable series is $\{Y_t\}$, the regression model is expressed as

$$Y_{\mathrm{t}} = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \varepsilon_t \tag{6}$$

where $\beta = (\beta_0, \beta_1, ..., \beta_k)$ are cointegrating vectors, ε_t is the regression residual. If the regression residual series ε_t is stationary, there exist cointegration between $\{Y_t\}$ and $\{X_1\}$, $\{X_2\}, ...\{X_k\}$. Therefore, the eventual aim of cointegration process is to identify the cointegration vector to ensure the residual series stationary.

For a stationary variable series $\{Y\}$, it is called integrated of order 0 if the variable itself is stationary, denoted as $\{Y\} \sim I\ (0)$. As for a non-stationary variable series, if it becomes stationary after d times difference operation, it is integrated of order d, which indicates d unit root is existed in series $\{Y\}$, denoted as $\{Y\} \sim I\ (d)$. To obtain the cointegration vectors β, the order of integration should be determined at the beginning, since the cointegration procedure can only operate for the non-stationary variables with the same order of integration. Subsequently, the cointegration vectors β can be computed from the cointegration test. The integration tests can be classified to regression parameter based method (such as Johansen test and so on) and regression residual based method (such as Engle-Granger test and so on).

In this respect, people have successfully addressed the challenge of environmental variation in structural time series data (Tomé et al.2020). For instances as shown in Fig. 7, Liang et al. (2018) propose a frequency-based cointegration technique to eliminate the influence of the changing environmental temperature and identify the structural damage, which is verified by a practical application on a cable stayed bridge. Fan et al. (2020)

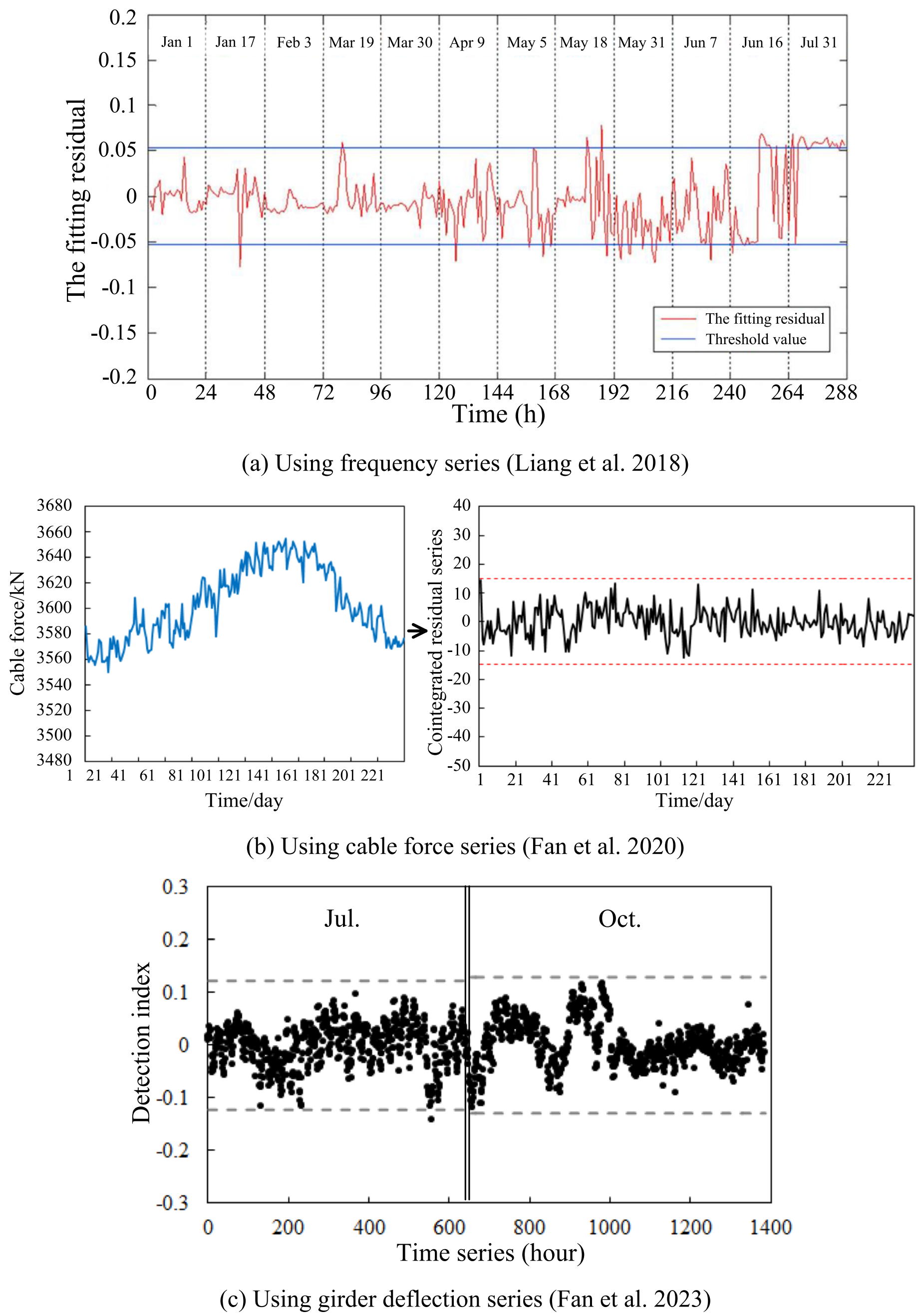

Fig. 7 Instances of cointegration adopted in anomaly detection. **a** Using frequency series (Liang et al. 2018).**b** Using cable force series (Fan et al. 2020). **c** Using girder deflection series (Fan et al. 2023)

introduced cointegration to cable anomaly detection. Specifically, linear combining two non-stationary time series using the cointegration algorithm is developed to produce a more stationary cointegrated residual series as warning index of cable force series, which is proved to be insensitive to the influence of environmental temperature. They also presented an application of the cointegration based method to detect anomalies deflection of a long-span suspension bridge (Fan et al. 2023).

4.2 The FE model based method

Structural anomaly detection based on the FE model is a research direction of large interest in the mechanical, civil, aerospace, etc., engineering fields, the FE analysis provides an effective approach of structural anomaly detection. In an intact structure with its FE model, structural anomaly, especially occurrence of damage and serious accident will locally alter the structure, hence lead to differences between theoretical FE analysis and structure actual status (Alkayem et al. 2018). Such differences can be reflected by deviations between the structural parameters of the FE model and structure incurring damage, or between FE analysis results and actual structure response (noted that the FE models should have been updated).

In view of the limitation of field validation, many FE model based anomaly detection methods for large span bridges have been conducted, that were also reported in publications (An et al. 2019). Relied on vertical dynamic response of the passing vehicles, Yin and Tang (2011) detected multiple simultaneous damages for a cable-stayed bridge by analyzing the differences between the damaged bridge and the healthy bridge, which can be called the relative displacement response vector of the vehicle. Zhong et al. (2016) proposed a multiscale FE model validation method that considering uncertainties of structural parameters and its propagation, the FE model was then used for structural damage prognosis. Based on the FE model updating, Niu et al. (2015; 2018) proposed a damage detection method by calculating element modal strain energy as a novel index, see Fig. 8. Xu et al. (2019) presented a practical multivariate linear-based model for separation of thermal effects from the responses of a large span cable stayed bridge, the weight coefficients (i.e., normalized response corresponding to various temperature actions) in the model were obtained by the FE simulation. On this basis, Fan et al. (2021) developed an anomaly dynamic warning method of cable-stayed bridges to help identify

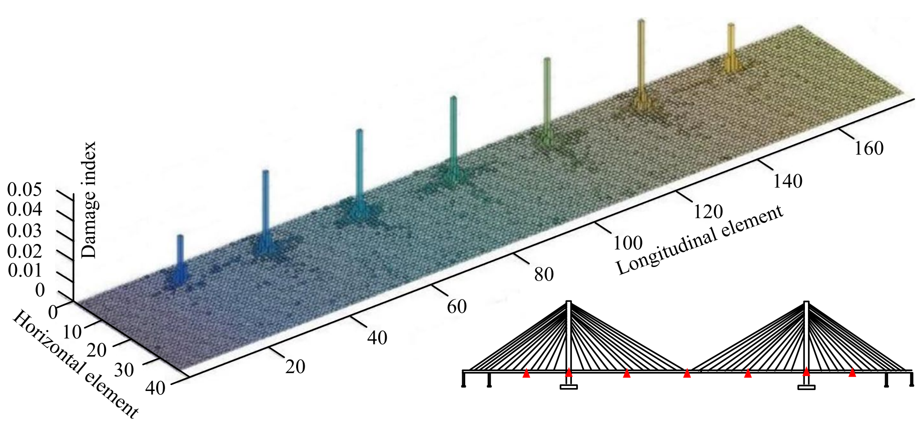

Fig. 8 The element modal strain energy index to detect damage (Niu et al. 2018)

emergencies in time and take inspection or maintenance decisions to ensure structural safety, see Fig. 9. It can be seen that the FE model based anomaly detection methods is similar to the model updating, for a FE model that representing the current structure is optimally determined using latest measurements.

However, these FE model based anomaly detection methods are somewhat inefficient in reflecting anomaly, since the updating of the FE model might not give a reasonable explanation of the changes in structural characteristics. In addition, the FE analysis of large span bridge means large calculation and data size, so that these FE model methods are more suitable for smaller civil structures (Zong et al. 2014).

4.3 The data driven method

The data driven anomaly detection methods rely on the input–output relationships between measurements. In recent years, with the development of structural monitoring technique (especially SHM systems) and data science (statistical theory, machine learning, deep learning, data mining technique, etc.), the application of these methods in large span bridges have attracted more and more attention. Besides, some applications combined data-driven and physics-based methods to achieve anomaly detection, it also provides an effective way. Main typical progress on this field is summarized as follows.

4.3.1 Regression analysis

The regression based methods are usually used to establish a relationship between temperature and structural response, for instance as shown in Fig. 10. Based on monitored temperature data and structural response data, the appropriate regression model (such as a multiple linear model) is selected to establish a statistical

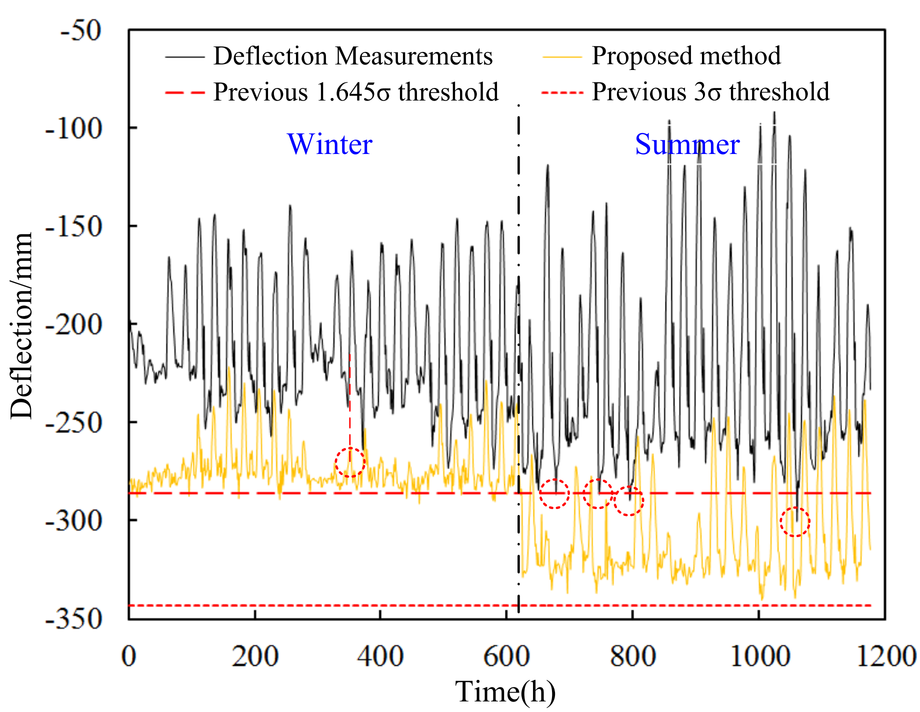

Fig. 9 The anomaly dynamic warning method based on FE model analysis (Fan et al. 2021)

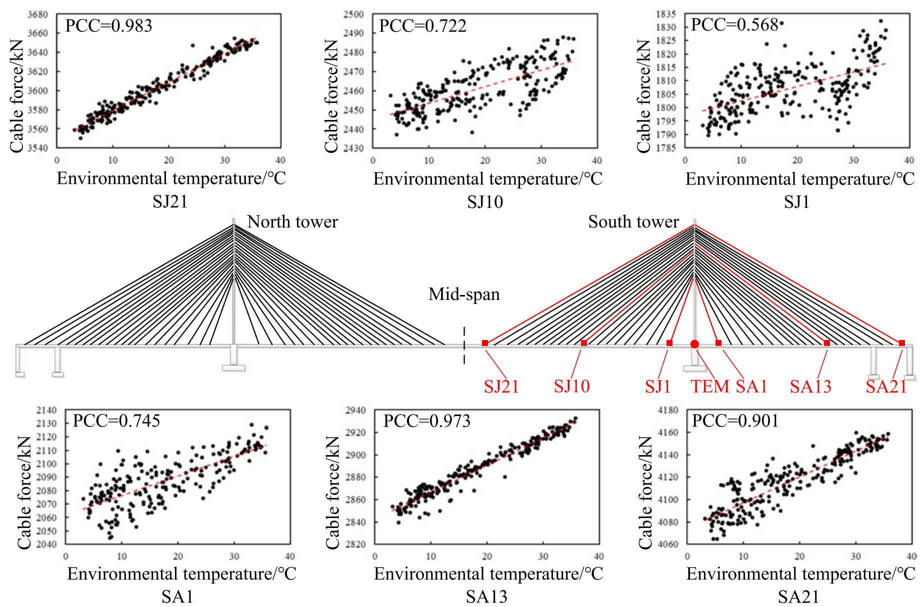

Fig. 10 Linear regression between temperature and cable force of a large span bridge (Fan et al. 2020)

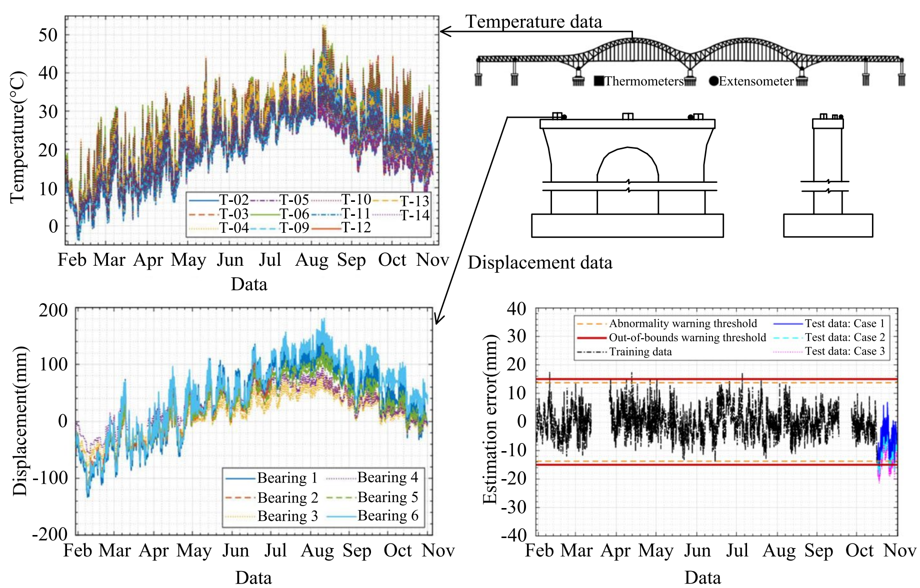

Fig. 11 Anomaly detection of bearing displacement (Wu et al. 2021)

model between them. Subsequently, anomaly detection can be carried out according to the established regression model, calculating the difference between the predicted temperature effect and the measured value as the indicator to alert large bridge structures. These methods are suitable for structural response data that have clear relationship with temperature, such as bearing longitudinal displacement (see Fig. 11), main cable deflection, etc.

4.3.2 Wavelet transform

In the field of structural anomaly detection, changeable operational temperature introduces great problems to relative researches, for signal fluctuation induced by structural anomaly may be covered by that due to environmental factors. Wavelet transform can be used to easily separate thermal responses from the raw monitoring data based on the periodicity of temperature action. The core idea of wavelet transform is to use a finite length or fast decay wave to reconstruct signals. A time-domain signal *f(t)* can be described as the convolution of a wavelet coefficient W_t and a wavelet function $\psi(t)$, wherein the wavelet function $\psi(t)$ can be expressed as:

$$\psi_{a,b}(t) = |a|^{-1/2}\psi\left(\frac{t-b}{a}\right) \tag{7}$$

where a and b are stretch parameter and translation parameters, respectively. The wavelet coefficient W_t presents the similarity between signals $f(t)$ and wavelet function $\psi(t)$, which is:

$$W_f = |a|^{-1/2}\int_R f(t)\,\psi\left(\frac{t-b}{a}\right)dt \tag{8}$$

Considering temperature action have significant periodicity, including the period of 24 h for diurnal temperature actions and the period of 1 year for seasonal temperature actions (Ding et al. 2009). Based on the definition of the wavelet transform, each signal decomposition corresponds to a certain bandwidth. The temperature induced structural responses are supposed to be confined within a specific bandwidth in frequency domain when conduct wavelet transform. Therefore, temperature induced response separation can be realized. Then, a threshold needs to be determined to detect anomaly, such as shown in Fig. 12. However, the judgment of the wavelet signal layer corresponding to the temperature response exists randomness and subjectivity (Xu et al. 2020a).

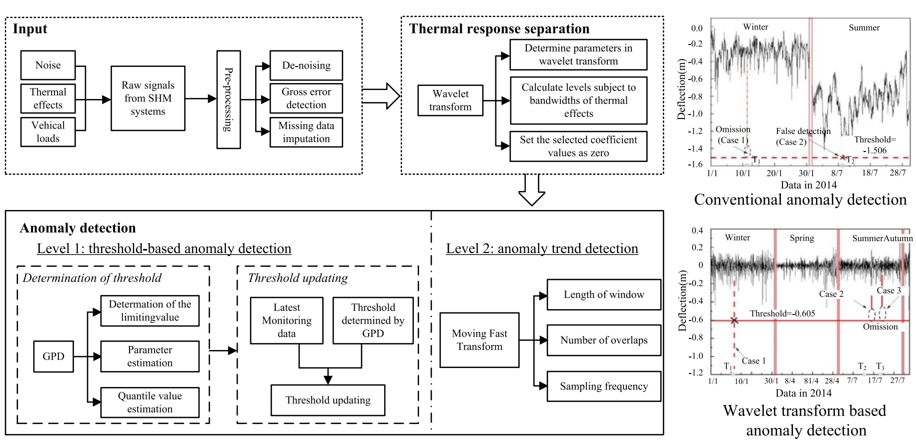

Fig. 12 Wavelet transform based anomaly detection (Xu et al. 2020a)

4.3.3 Principal components analysis (PCA)

The PCA does not require to measure environmental parameters, the main idea of PCA is to eliminate the contribution due to environment by removing linear correlations among the data. It uses linear transformation to decompose data into a series of principal components and compress the original data while preserving most of the information present in the data (Bellino et al. 2010). In the application of bridge anomaly detection, the purpose can be realized by separating linear correlation terms in data and eliminate the influence of environment. However, the PCA method are usually suitable for Gaussian distribution data. In view of the structural nonlinearity and measurement noise, the monitoring data of a bridge often shows non-Gaussian distribution characteristics. In addition, since the PCA is basically a linear tool, it is hard to treat many cases which the relationship between couples of features is nonlinear. Hence, some modifications of the algorithm have been proposed, as for example the local PCA and the moving PCA. A typical moving PCA method for anomaly detection is shown in Fig. 13 (Zhu et al. 2019). The results showed that these improved PCA methods are more efficient and suitable for anomaly detection (Posenato et al. 2008).

4.3.4 Bayesian inference

Bayesian inference, as an effective analytic tool in quantifying uncertainties, has been increasingly adopted to update model, identify system, detect anomaly, and diagnose sensor faults (Ni et al., 2020; Xu et al. 2021; Zhang et al. 2021). The essential of Bayesian inference is to combine Bayesian theory with new evidence and prior probabilities to

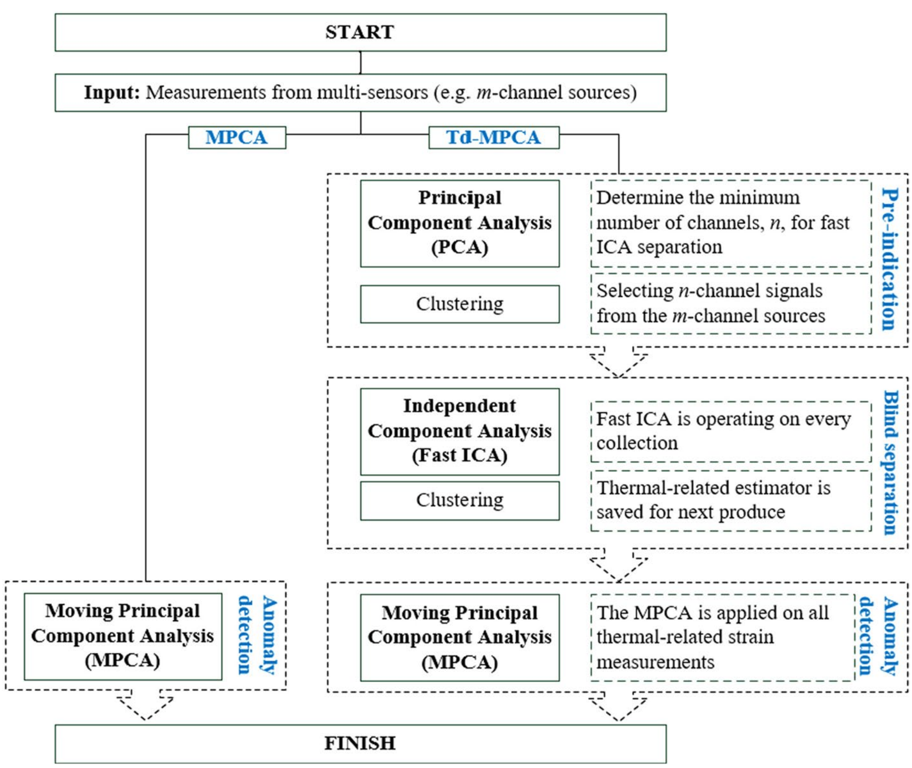

Fig. 13 The moving PCA method for anomaly detection. (Zhu et al. 2019)

infer the posterior probabilities. When introduced to anomaly detection, the Bayesian inference is often used to estimate the parameter distribution of prediction models to consider their uncertainty. For instance, Ni et al. (2020) used Bayesian inference to estimate the parameter distribution of a linear regression model of temperature and girder end displacement, then achieve anomaly detection based on the established prediction model. Ren et al. (2022) proposed an anomaly pattern detection method considering the time-varying temperature displacement relationship, the Bayesian estimation was used to determine the distributions of the parameters in the defined pattern, hence measure the uncertainty in the anomaly detection, see Fig. 14. This method has a high detection rate and low false detection rate for the anomalous bridge boundary condition. Xu et al. (2023) proposed a multi-index probabilistic anomaly detection approach for large span bridges based on Bayesian estimation and evidential reasoning to measure uncertainties within anomaly detection and distinguish sensor faults from anomalous events. In view of the structural damage is not a common event in real condition, the sparse Bayesian learning has also been used to detect structural anomaly, which has been found can improve the accuracy of damage identification (Hou et al. 2020a, b; Li et al. 2021).

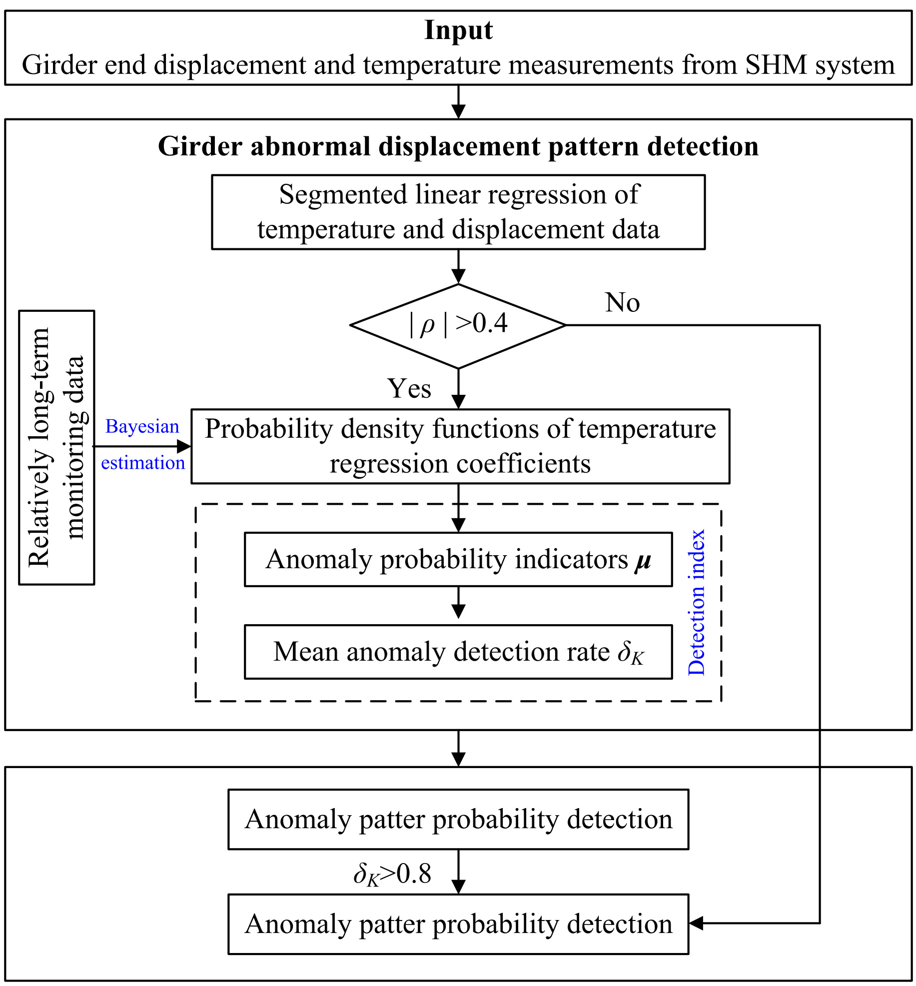

Fig. 14 The anomaly detection process involves Bayesian inference (Ren et al. 2022)

However, the sparse Bayesian learning method still should be validated on actual large span bridge structures. In general, there are not many applications of anomaly detection methods based on Bayesian inference at present, further research is needed.

4.3.5 Machine learning

The advancement of information technology and intelligence algorithms has brought the era of machine learning. Machine learning is classified as artificial intelligence, that focuses on teaching computers how to make predictions (output) from available datasets (input) and algorithms. The application of machine learning, e.g., neural networks (NN), decision tree (DT), support vector machine (SVM), random forest (RF), etc., is very broad in different areas including structural engineering (Thai 2022). Figure 15 is the typical machine learning procedure. Machine learning can be divided into supervised, semi-supervised, and unsupervised groups, depending on the learning process. Among them, the supervised learning is the most basic type whose algorithm is trained from a labelled dataset. This method is suitable for classification problems, hence it has been widely used in structural anomaly detection (Flah et al. 2021). Hakim and Razak (2013) used adaptive neuro-fuzzy inference system (ANFIS) and artificial neural networks (ANNs) techniques to identify damage in a model steel girder bridge, the performance of two methods was compared. Neves et al. (2017) presented a model-free damage detection approach of the steel girder based on artificial neural networks. In load pattern recognition and load effect analysis, Li et al. (2018) proposed a data-driven approach using the machine learning scheme based on a database of 6 years field measurements to recognize anomalous vortex-induced vibration modes in a long-span suspension bridge. Xin et al. (2020) combined wavelet analysis and transfer deep learning proposed a status-driven acoustic emission (AE) monitoring convolutional neural network (CNN) method, the relationship between AE signals results and cable status was constructed to identify fracture AE signals, as shown in Fig. 16. Using isolation forest based on decision trees, Sun et al. (2023) developed a complete condition assessment approach for constraint devices using girder end displacement measurements, which includes four steps, namely, data preprocessing, feature characterization, datasets splitting, and anomaly detection (see Fig. 17). The machine learning methods are also adopted to quantify the severity of damage, for instance, width and length of cracks on bridges can be identified by machine learning based on extensive sample images (Zhang et al. 2022a, b).

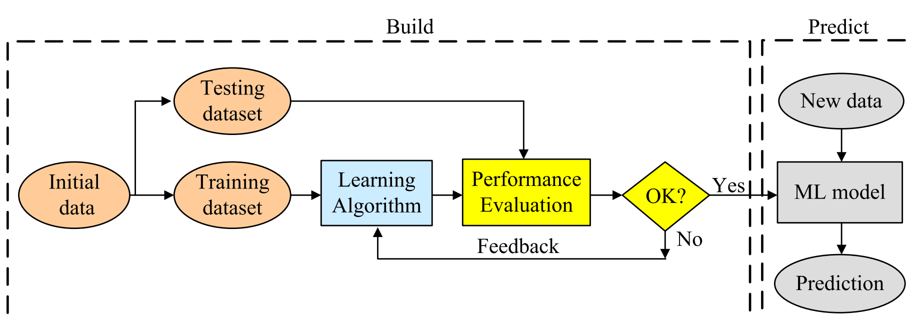

Fig. 15 The typical machine learning procedure (Thai 2022)

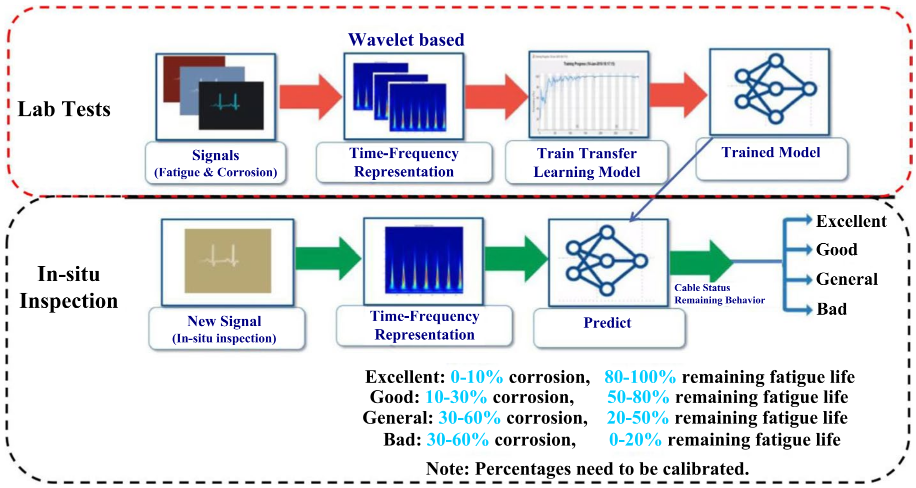

Fig. 16 The status-driven AE monitoring CNN method to detect cable fracture (Xin et al. 2020)

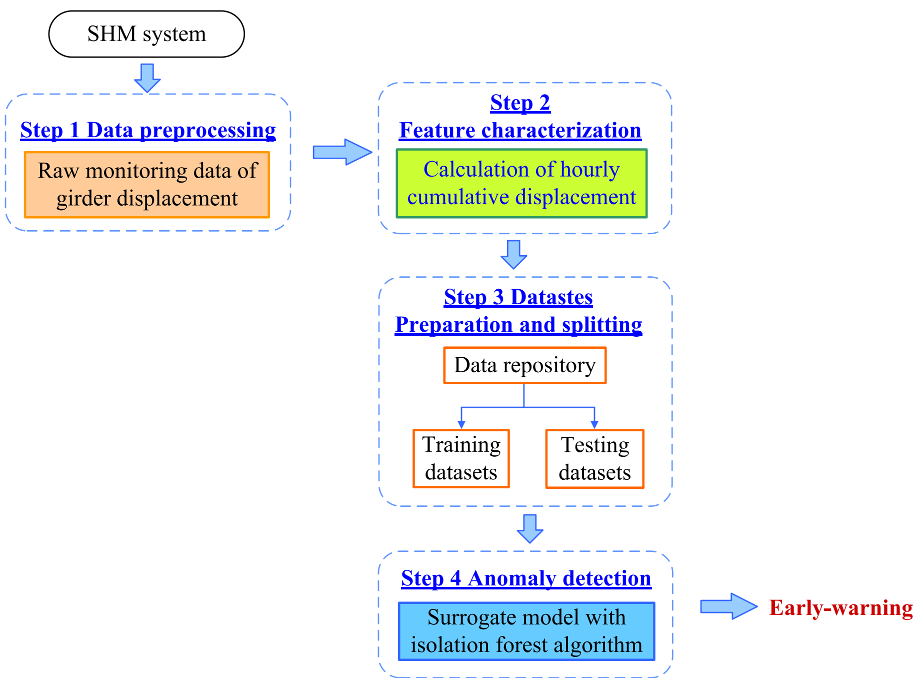

Fig. 17 The data-driven isolation forest to detect damper malfunction (Sun et al. 2023)

However, the machine learning based methods also have limitations, such as requirement for too much training data sometimes, and a lot of computing time and power is needed when the machine learning models are complex (Azimi et al. 2020; Karimi and Mirza 2023). Besides, it is necessary to improve the accuracy and performance of available methods. The practical application of machine learning in structural anomaly detection is still in its infancy.

4.3.6 Digital twin

Digital twin is a simulation process that fully utilizes data resources to reflect the operation of the corresponding real system. Table 1 presents the 5 main characteristics of digital twin and their descriptions (Jones et al. 2020; Tang et al. 2023). For digital twin of a bridge, it contains a virtual replica of a real world bridge entity and a connection that allows both the real and virtual assets to be synchronized along the life cycle of the structure (Rios et al. 2023). The SHM system can provides continuous data about the operational environment, loads and response of the structure to those loads. Therefore, it is reasonable to use the virtual model to infer the response of the real bridge entity to load (Zhao et al. 2022). A series of anomaly and degeneration scenarios can be simulated on the virtual replica, which will reproduce the structural response of its real counterpart through geometry models or FE models. Subsequently, the anomaly detection method can be developed based on testing the bridge and generating the required data under normal and damaged scenarios. However, there still exists great challenges and limitations in real practice of digital twin, it is expected to play an important role in bridge anomaly detection in the future.

5 Summary of recent progress and future trends

A comprehensive review of the anomaly detection in large span bridges, including concerned parameters, various data sources and available methods are presented above. Based on the results of this review, the following findings can be summarized as below:

- The dynamic structural vibration parameters including vibration mode, frequency and damping were initially utilized to identify the structural anomaly, which were found often difficult for these large and complicated bridges. At present, more attention has been paid to vulnerable components of a large span bridge, e.g. steel girder, constraint devices at girder end, stay cables or suspenders, hence the measured positions were set on these components directly. Many static parameters that reflect bridge performance were now adopted to detect structural anomaly from various aspects, which helps to improve the sensitivity of the anomaly detection methods.
- The FE model of large span bridges developed by modelling software has been widely used to analyze structural characteristics in various conditions and then provide simulated data. Many anomaly detection methods require an accurate FE model of the bridge. It is necessary to modify or update the original FE model with in-site measurements. Technology in this field has matured considerably over the

Table 1 The 5 main characteristics of digital twin

Characteristic	Description
Physical Twin	The physical entity existing in the physical environment
Virtual Twin	The virtual entity existing in the virtual environment
Physical Environment	The environment within which the physical entity exists
Virtual Environment	The environment within which the virtual entity exists
State	The measurements for all parameters corresponding to the physical/virtual entity and its environment

past several years. However, considering the computing time and power, multi-scale FE models have stronger competitive advantages for complicated large span bridges.

- The SHM techniques have been increasingly applied in large span bridges worldwide by installing various sensors. Analyzing the accumulated SHM data and improving the data quality to realize anomaly detection have also naturally become a priority of SHM research. By now, with the recent progress in data acquisition, data transmission, data process tools and algorithms, researchers can interpret data, detect faults, and even recover lost-data. The extensive collected SHM data provide chances to detect bridge potential anomaly an unprecedented chances and resources. Besides, various inspection methods, such as radar, sonics, ultrasonic tomography, acoustic emission, etc., also provide effective information for anomaly detection.
- In view of data related to large span bridges are usually collected and saved in the time domain, the time series analysis methods are easily adopted to detect anomaly and assess the performance of the bridge, since the coefficients or residuals obtained from time series analysis process contain plentiful structural information. Many classical time series models such as AR model, MA model, ARMA model, and ARIMA model have widely used to judge the structural status. These time series models were found to be suitable approaches to estimate the performance changes of the structures in the time domains during the service period. Some novel methods based on time series theory were also utilized, for instance, recent studies showed the cointegration technique can be applied to remove environmental effects from bridge SHM data, its crucial idea is to create a stationary residual based on the nonstationary variables in normal conditions and then detect the anomaly through the behavior of the residual.
- In view of the limitation of field measurement, FE model based anomaly detection methods for large span bridges have been adopted. The differences between theoretical FE analysis and structure actual status induced by structural anomaly, especially occurrence of damage and serious accident can be reflected by deviations between the structural parameters of the FE model and structure incurring damage. The accuracy of the established FE model has a significant impact on anomaly detection. Therefore, it is recommended to further study anomaly detection methods with low dependence on accuracy of structural FE models to reduce workload of model establishment and updating. In addition, for large span bridges, further research is needed to develop the multi-scale FE models, which include a global bridge structure and one or several refined local models.
- Advances in intelligence algorithms, especially the machine learning, revolutionized structural anomaly detection. Compared with traditional methods, these data driven methods not rely on complicated FE models or visual inspections. The critical procedure is to establish an input–output relationships between measurements. Consequently, the data driven methods have demonstrated versatility and now become the most attractive approaches, it also bears new promise in the fields of structural anomaly detection. However, the data driven methods' sensitivity to slight structural damage and anti-noise ability are still required to be improved.

Despite the recent progress of anomaly detection for large span bridges, every proposed approach still has its limitations, it indicates that anomaly detection of complicated bridge structures is a difficulty, and additional works are needed to promote further theory, methodology and applications. In this paper, several future trends are summarized as follows:

- *Probabilistic anomaly detection:* Most of current anomaly detection methods inevitably suffer uncertainty, such as uncertainty of monitoring data, uncertainty of FE model, processing errors, etc. It may influence the effectiveness of detection results, hence make wrong decisions about bridge maintenance (Xu et al. 2022). The probabilistic anomaly detection methods that can reduce the influence of uncertainties should be developed in the feature.
- *Distinguish structural anomaly and sensor fault:* When use the bridge SHM data to detect structural anomaly, it often coupled with sensor fault. Most current anomaly detection methods are hard to distinguish them. It is necessary to develop more intelligent algorithms to identify anomaly in SHM data that induced by structural damage or serious accident effectively.
- *Multi-indexes based anomaly detection:* Current anomaly detection methods were developed based on a single detection index. However, each detection index has its specific applicability, considering the sensitivity to different abnormal conditions. For instance, dynamic parameters such as vibration frequency are more suitable for bridge global performance while stress measurements are more suitable for bridge local damage. The multi-indexes based anomaly detection method will make full use of different monitoring data to optimally achieve large span bridge anomaly detection. Meanwhile, the information fusion and evidential reasoning are suggested to be used to handle the analysis results to improve its effectiveness.
- *Machine learning based methods:* As a rising technology, machine learning based methods show great potential. Further investigations of employing machine learning technique in bridge anomaly detection are encouraged. Specifically, physical explanation of machine learning models, efficient management of such massive and heterogeneous data, extracting new potential features, visualization of detection results, and facilitating practical use in structures.

6 Conclusions

This paper presents a systematic overview of anomaly detection in large span bridges The following main conclusions can be drawn.

1. The usually concerned structural parameters for anomaly detection of large span bridge were analyzed based on previous researches, including parameters and dynamic static parameters, such as vibration parameters, girder deflection, cable force, structural strain, and girder end displacement.
2. Basic data for structural anomaly detection were analyzed. It was found that the FE analysis data, SHM data, and various inspection results were main data source, wherein the SHM data is the most widely used in current research.

3. Anomaly detection methods of large span bridges adopted in existing studies were discussed. Existing studies in this field were divided into time series analysis based methods, FE model based methods, and data driven methods. Each methods have its advantages and disadvantages. Some advanced new approaches have also been developed to improve the anomaly detection efficiency or achieve specific purpose, however, more practical applications are needed.
4. The summary of this review could contribute to development of more efficient anomaly detection methods for large span bridges. Many notable large span bridge accidents have occurred in recent years, highlighting the necessity of enhancing current research and provoking new research needs. The importance of further studies related to probabilistic analysis, coupling structural anomaly and sensor fault in monitoring data, multi-indexes system, and machine learning technique are addressed to keep pace with engineering needs.

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Authors' contributions
Ziyuan Fan reviewed related literatures and wrote the main manuscript. Xiaoli Tang and Yuan Ren established the framework and advised the summary. Yang Chen and Chao Deng revised the manuscript. Zihang Wang, Ying Peng and Chenghong Shi collected information and provided worthy advice. Qiao Huang reviewed and supervised the manuscript. The author(s) read and approved the final manuscript.

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Availability of data and materials
Not applicable.

Declarations

Competing interests
All authors declare that there are no competing interests.

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