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Health monitoring of long-span bridges using deep learning driven by sensor measured and numerical response data

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ABSTRACT: Both the vibration and quasi-static load responses of cable-stayed bridges affect their long-term behaviours (eg in fatigue) and so their structural integrity. The associated modal behaviours and (owing to their statically indeterminate nature) the static response are strongly influenced by the spatial stiffness profiles of the bridges. Translation into loads and response of data from a comprehensive network of multi-sensors, shows huge potential to drive a deep learning (DL) approach which can identify these spatial stiffness profiles, and so can reveal any spatial stiffness perturbations arising from any damage states. The role of sensor-verified FE analysis is discussed in providing a means to assess likely damage states for training the DL approach to enable the early defect detection. A significant impact of data quality and sample size on the DL method is discussed in the paper. This paper compares generation of data sets, establishment of learning frameworks, and performance of each DL application. A review of existing literature in the wider field of SHM is also provided, to strengthen the case for this novel approach.

1 INTRODUCTION

With the continuous construction of long-span bridges, bridge damage caused by dynamic problems becomes an increasingly important consideration. Accidents caused by dynamic load, such as seismic load, wind load and passing vehicle load are common during bridges' service period. The Viadotto Polcevera bridge in Italy collapsed during a rainstorm on 14 August 2018, lead to forty-three people deaths. The Silver bridge crossed Ohio River in U.S. collapsed under the weight of rush-hour traffic on 15 December 1967, resulting in the deaths of forty-six people. Damage detection technology is crucial to preventing these serious bridge accidents.

Over the years, with the rapidly development of computer-based technologies, structural damage detection methods have evolved from the traditional visual inspection to the modal parameter identification (Salawu et al. 1997), (Pandey et al. 1991), (Sampaio et al. 2003) to the CNN-based image recognition method (Sandeep Sony et al.). To this end, due to its low cost and high accuracy, vibration-based deep learning is increasingly popular in recent years (Avci et al. 2021).

In the structural health monitoring of large civil structures, the application of deep learning method driven by monitoring data of sensor networks in damage identification has also attracted great attention of researchers. Deep learning networks were presented that they have better performance than shallow learning (like support vector machine) while processing data mining under noise effects (Lin et al. 2018). Another review is provided of the application of deep learning in SHM, including the vibration method and visual processing method (Azimi et al. 2020). Meanwhile, new technologies are being introduced that are aimed at identifying SHM damage, such as sensors and UAVs. The damage detection methods of bridge structures based on big data and artificial intelligence methods in recent years are summarized (Sun et al. 2020).

A review of the papers that have been published most frequently during the past decade is presented in this paper. The purpose of this review is to provide an overview of bridge SHM, and DL techniques (Convolutional neural network methods are mainly focused on in this paper) in defect detection, summarize the most recent research developments, and discuss future directions. Following is a description of the paper's structure. In section 'Bridge structural

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health monitoring', This paper discusses first the types and locations of potential defects in long-span bridges, then it introduces the sensor networks in SHM systems. In section 'Vibration-based defect detection', it mainly focuses on structural defect detection method using DL method driven by time series vibration data. The generation of damage data sets is the core content of deep learning damage detection. In this section, the methods for generating damage data sets are divided into three categories, including vibration testing, numerical simulation, and the combination of vibration testing and numerical models. The performance of deep learning models in different applications is discussed respectively. Section 'Summary and prospects' discusses the limits, challenges, and future trends of structural defect detection using DL method.

2 BRIDGE STRUCTURAL HEALTH MONITORING

2.1 *Defect of long-span bridge structures*

Cable stayed bridges are the most widely used long-span bridges in the world. a cable-stayed bridge is mainly composed of the main girder, pylons and stay cables. Figure 1 shows the axial force paths in a cable-stayed bridge. The main girder is generally a composite steel-concrete structure, the pylons are mostly concrete structures, and the stay cables are made of high-strength materials.

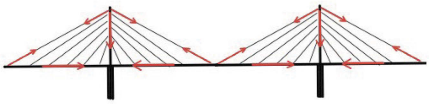

Figure 1. Force paths of cable-stayed bridges.

As to the cables, continual exposure to environmental factors will cause corrosion of steel, which will result in cracks or even fractures in the cable. As a result, it can seriously degrade the stress state of the cable-stayed bridge. Furthermore, the stiffness of the cable is low, making it easy for external loads to cause vibration. Vibrations of this intensity will accelerate the abrasion of the anti-corrosion coating on the cable and aggravate the corrosion of the cable. Vibrations will also accelerate the development of original defects. Stay-cables and its anchoring details are the most common positions for defects (Pulkkinen et al. 2015).

The main girder of long-span cable-stayed bridge is usually composed of steel-concrete. Contact with soil and water will also cause corrosion of the main girder exposed to the air. Furthermore, vehicle overloads and traffic accidents may damage the structure locally, causing cracks and peeling of the main girder surface. In addition, the changes in cable force and the deflection deformation of the pylons will also cause the structural damage of the main girder.

The pylons of the cable-stayed bridge are usually composed of concrete. Common defects of the pylon include deflection deformation, fatigue crack and shear crack. Natural load like wind and unbalanced tension between cables can cause pylons to deflect. In the anchorage area of the cable, frequent changes in cable force and temperature can lead to fatigue cracking of the concrete. The shear crack usually caused by bridge state changes. The shear crack was discovered on the Viadotto Polcevera bridge collapsed in 2017 (Sandberg et al. 2010).

According to above, the stay cable is the most susceptible to damage in a long-span cable-stayed bridge, followed by the main girder and the pylons. It is corrosion and fatigue cracking that cause the majority of damage to structures. To study fatigue damage on long-span bridges, a 1:4 suspension bridge model was developed in 2019 (Zeng et al. 2019), the model includes the main cable, anchorage zone, hanger, and box girder. Fatigue experiments were applied to the model. The high-strength steel wires of the hangers were gradually evolving into a fatigued state after 2 million loading cycles, and some of them broke after 2.4 million loading cycles. The hanger wire lost transfer force ability after 2.8 million loading as a result. This shows that the early fatigue damage in the cable will gradually accumulate over time and eventually lead to structural failure.

According to an analysis of the fatigue damage in the bridge by establishing the finite element model of Tsing Ma bridge (Chan et al.2015). The FE model was updated by comparing the modal characteristics identification results based on measured data (using SHM system on the Tsing Ma bridge) and FE model results. It is found that the stress spectra in the elements were reduced when considering fatigue damage effects.

The defects of long-span cable-stayed bridges have strong randomness, which brings challenges to the damage detection and maintenance of bridges (Sandberg et al. 2010). A sea crossing cable-stayed bridge was detected that the shortest cable near the pylon was overstress. In 2004, fatigue cracks were detected in new cables after the first round of maintenance and a small amount of cable replacement in 1999. The condition of only a small number of cables is monitored by an acoustic monitoring system, which is not capable of accurately assessing the health of the remainder. In order to ensure safety, all remaining cables were replaced as part of the project.

In conclusion, it can be observed that a method of accurately detecting damages to key parts of a cable-stayed bridge is extremely important for ensuring the safety of the bridge.

2.2 *Long-span bridge sensor networks*

The interest in structural health monitoring (SHM) has grown in order to objectively manage civil infrastructure systems. Use of a long-term SHM can enable determination of structural property changes over a long period of time, by either continuous monitoring or by intermittent live load tests. The health of a bridge is monitored by the use of sensors that measure external loads, dynamic responses, etc. For instance, strain gauges were used to infer the biaxial response to live loads in a bridge with reduced transverse distribution capability (Sebastian et al. 2018).

Over the past few decades, a large number of newly built long-span bridges have been equipped with rich sensor networks for real-time monitoring of environmental response and response signals on bridges. It provides a valuable and large database for the condition description of bridges.

Table 1 lists several SHM sensor networks installed on the bridges opened in recent decades. The rich sensor network provides a barge bank of sensor data that enables quantification of both the loads and the associated responses, both traffic and environmental loads can be assessed.

Table 1. SHM sensor networks of long-span bridges.

Long-span bridge	Open year	Length of main span	Number of sensors	SHM sensor networks*									
				Acc	Str	Dis	Tem	Cor	DWIM	GPS	Ane	Til	Bar
Sutong cable-stayed bridge	2008	1088 m	1000	☑	☑	☑	☑	☑		☑			
Stonecutters Bridge	2009	1018 m	1505	☑	☑	☑	☑	☑	☑	☑	☑		☑
Queensferry Crossing Bridge	2017	2*650 m	2280	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑
Ting Kau Bridge	1998	475 m	238	☑	☑	☑	☑		☑	☑			
Kap Shui Mun Bridge	1997	430 m	272	☑	☑	☑	☑			☑	☑		
Jindo cable-stayed bridge	1984	334 m	113	☑	☑		☑				☑		
Charles W. Cullen Bridge	2012	289 m	144	☑	☑	☑					☑	☑	

* Accelerometer (Acc), Strain gauge (Str), Displacement transducer (Dis), Temperature and humidity sensor (Tem), Corrosion system (Cor), Dynamic Weigh-in-Motion system (DWIM), GPS, Anemometer (Ane), Tiltmeter (Til), Barometer (Bar)

3 VIBRATION-BASED DEFECT DETECTION

3.1 *Deep learning-based defect detection method*

Structural health monitoring (SHM) is a promising technique, it can identify the presence, severity and location of any damaged areas by analysis of recorded signals in various forms.

Convolutional neural network (CNN), as an important branch of deep learning, can be used to automatically discover various features in large raw datasets by backpropagation algorithm, it can reduce both research time and expert knowledge of physical problems.

With rapid advances in deep learning technology, the structural health monitoring community has witnessed a prominent growth in deep learning-based condition assessment techniques of structural systems. Deep learning has ushered in many breakthroughs in vision-based detection via convolutional neural networks (CNNs), but the vibration-based structural damage detection by CNN remains being refined. Thus, a fast and accurate structural damage detection system using one dimensional (1D) CNNs was presented in recent years. One major advantage is that a real-time and low-cost hardware implementation is feasible due to the simple and compact configuration of 1D CNNs. Figure 2 illustrates the flow chart of a typical CNN model training process.

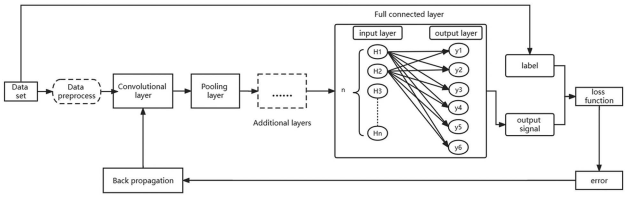

Figure 2. A CNN training flow chart.

Convolutional layers extract features, pooling layer reduces the dimension of the data, and a full connection layer classifies the input signal, then compares it to a preset label to determine the loss function. Trained models with a lower loss function have a higher classification accuracy.

Next, according to different methods of generating damage data sets, the structural damage detection based on CNN method will be introduced in three categories: vibration test, numerical simulation, and using numerical simulation together with vibration test. The content includes the characteristics of each study, the unique CNN model stratification, the existing shortcomings, etc.

3.2 *Vibration test*

CNN training requests a damage dataset with a large capacity. Only if the damage can be easily added to the structure, a large number of damage data can be collected through vibration tests at low cost. Using loosened bolts is a repairable method to applying damage in steel structures (Osama et al. 2017). Damage at the steel frame can be simulated by loosening the bolts at joints. A modal shaker excited the structure, and acceleration signals were collected at the joints.

Figure 3 shows an effective way to increase the capacity of the dataset by slicing the signal with overlay. To that end, in their follow-up research (Onur et al. 2018), the acceleration sensors in the experiment was replaced by wireless sensors with a computationally low cost. On this basis, they represented a 1D-CNN-based damage detection method with only two experiments (Osama et al. 2018): test on undamaged structure and test on fully damaged structure. This method can enable judgement as to whether the structure is damaged under the condition of limited damage data.

Adding extra mass blocks is another way to applying repairable damage to real structures. A three-span reinforced continuous beam bridge was established using the finite element method (He et al. 2020). As part of this study, the damage was simulated by loading extra block masses (20kg and 40kg, respectively) where it is expected to occur (close to the mid span). Experiments conducted on the beam at both a laboratory scale and in a numerical model show that this method accurately predicts damage along its middle span.

A similar method to obtain the damage data of a steel girder bridge (Zhang et al. 2019). According to the results, the proposed CNN model is sensitive to tiny local mass changes at 8 different positions of the in-lab steel beam structure. It can greatly detect the tiny mass changes.

At the end of this section, Table 2 summarizes the CNN-based defect detection approaches that generate damage data sets through vibration tests, including the applied excitations, the various types of damage, the dataset capacity, and the performance of the defect detection.

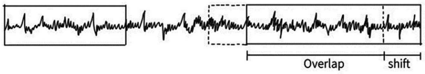

Figure 3. Data augmentation method.

Table 2. Review of CNN-based defect detection methods, datasets collected by vibration tests.

Ref	Test structure	Type of damage	Data generation	Dataset capacity	Performance
(Osama et al. 2017)	A 4.2m length steel grandstand simulator	Loosen the bolts at beam-to-girder connections	Random shaker excitation	12288 acceleration samples	Damage identification and damage localization
(Onur et al. 2018)	A 4.2m length steel grandstand simulator	Loosen the bolts at beam-to-girder connections	Random shaker excitation	5280 acceleration samples	Damage identification and damage localization
(Osama et al. 2018)	A 3.6m height four-story steel benchmark frame	Loosen the bolts and remove the brave members	Random shaker excitation	8988 acceleration samples	Damage quantification
(He et al. 2020)	A 9.8m length girder bridge	Adding additional mass blocks	Random shaker excitation	800 acceleration samples	Damage localization and quantification
(Zhang et al. 2019)	A 2.09m steel beam (S1), a 6.45m girder bridge (S2) and a 27.3m long girder bridge (S3)	Adding additional mass blocks	Random shaker excitation (S1 and S2), white noise excitation (S3)	14465 acceleration samples (S1), 8595 samples (S2), 4800 acceleration samples (S3)	Damage localization and quantification

3.3 *Numerical simulation*

For structures in service, it is often difficult to obtain the data set under damage state, which brings difficulties to the training of deep learning model. In this case, numerical models provide damage simulation and data generation efficiently. As to a rectangular section beam with 40 beam elements, damage cases can be easily simulated by reducing the local stiffness of beam elements (Guo et al. 2020). In total of 1.5×10^6 samples were generated for training and 5×10^4 samples for validation. This method is robust to data loss and noise interference, and the damage location and damage degree can be well detected.

It should be noted that the actual structure of the application often has errors with the model used in training. Therefore, the randomness of structural parameters should be taken into account when establishing the finite element model (Yulin et al. 2021). With the enhancement of noise, the accuracy of the model considering the randomness of structural parameters in training is significantly higher than that of the model without randomness.

The damage was also simulated by reducing the stiffnesses of the beam elements in a three-span continuous concrete beam (Yang et al. 2021). As stiffness and flexibility are reciprocal, when a structure is damaged, the local stiffness will decrease and the local flexibility will increase. This article briefly introduces the application of CNN method in prestressed concrete structures.

Due to the difficulty in extracting damage-sensitive and noise-resistant features from the response of structures, structural damage detection remains a challenging problem. It has an excellent performance of the deep learning method in detecting damage under the influence of noise in the data set (Lin et al. 2017). In this basis, to gain a physical understanding of how the network works, hidden layers were visualized in the network.

As the main weighing component of long-span bridge, the health of the cables largely determines the health state of the bridge. The Fourier amplitude spectra (FAS) of acceleration responses are used without extensive pre-processing for modal identification directly from the raw measurement data (Duan et al. 2019) (Chen et al. 2021). According to their results, the current CNN has been shown to be robust under a variety of observational noise levels and wind speeds.

At the end of this section, Table 3 summarizes the CNN-based defect detection approaches that generate damage data sets through numerical simulations.

Table 3. Review of CNN-based defect detection methods, datasets generated by numerical simulations.

Ref	Test structure	Type of damage	Data generation	Dataset capacity	Performance
(Guo et al. 2020)	A numerical model of Euler-Bernoulli beam	Reduce the stiffness of local beam elements	Gaussian white noise excitation	1.5*10^6 mode shape samples	Damage localization and quantification
(Yulin et al. 2021)	A 2m length simply supported concrete FE beam model	Reduce the stiffness of local beam elements	Random hammer excitation	20000 acceleration samples	Damage localization and quantification
(Yang et al. 2021)	A 55m length continuous beam bridge	Reduce the stiffness of local beam elements	No excitation, analyzed by ANSYS	Flexibility diagonal curvature as samples	Damage localization and quantification
(Lin et al. 2017)	A 10m length simply supported beam	Reduce the stiffness of local beam elements	Random white noise excitations	6885 acceleration samples	Damage localization and quantification
(Duan et al. 2019) (Chen et al. 2021)	A 2-D FE model of a 140m length tied-arch bridge	Decrease the cross-sectional area	Wind force excitations	28950 Fourier amplitude spectra samples	Damage localization and quantification

3.4 *Combination of numerical simulations and vibration tests*

It is easy and efficient to acquire damage data when a numerical model is established. A major problem is the failure to match the numerical model to the original structure, which may lead to a reduction in data quality. Hence, using the data from actual structural experiments used to update a numerical model, it is available to efficiently enhance the fidelity of the numerical model, then to accurately simulate a wide range of damage data (Franchini et al. 2022).

The updated numerical model can be used to generate recurrence graph for CNN training (He et al. 2020). However, the proposed method is an image recognition method in essence. The vibration signal is converted into a recursive graph, and then the damage is detected by image recognition. This will lead to complex computation for large structures.

In order to ensure the fidelity of the dataset generated by Finite element (FE) models, it's necessary to consider various uncertainties, including modeling errors, measurement errors, and environmental noises based on FE model and real intact state (Zohreh et al. 2020).

In order to ensure the fidelity of damage dataset generated by numerical models, it is also necessary to compare the modal parameters of actual structure and numerical model under damage conditions (Hakim et al. 2015). The damage in the experiment can be achieved by introducing a slot in turn obtained by grinding from the different locations of the structure. Meanwhile the damage was simulated by reducing the local stiffness in FE model.

The measured data from the vibration experiment as well as the data generated by the finite element model can both be used as input signals when training the deep learning model, which further guarantees the fidelity of the dataset (Teng et al. 2019). In this study, the data set required for CNN training was generated through the finite element model, and then the training results were verified by the data collected from the laboratory scale structure.

Table 2 summarizes the CNN-based defect detection approaches that generate damage data sets through the combination of numerical simulations and vibration tests.

Table 4. Review of CNN-based defect detection methods, datasets based on numerical simulations & vibration tests.

Ref	Test structure	Type of damage	Data generation	Dataset capacity	Performance
(He et al. 2020)	A 9.8m length girder bridge and a 75m length FE model	Reduce the local stiffness, load additional mass blocks	Random hammer excitation (Exp), noise excitations (FE)	800 recurrence graph samples (Exp), 10000 samples (FE)	Damage localization and quantification from 10 structural states
(Zohreh et al. 2020)	A 2m heigh jacket structure and its FE model	Remove the diagonal braces	Shaker excitations (Exp), noise excitations (FE)	500 FRFs samples (Exp), 1500 samples (FE)	Damage localization from 5 structural states
(Hakim et al. 2015)	A 3.2m length steel I-beam structure and its solid FE model	Grinding the structure (Exp), remove solid elements (FE)	Random shaker excitations (Exp), modal analysis (FE)	104 sets of mode shape value samples (52 Exp), (52 FE)	Damage localization and quantification from 101 structural states
(Teng et al. 2019)	A 10.62m length steel frame with 381 rods and its FE model	Cut rod section (Exp), reduce the stiffness of the rods (FE)	Hammer excitations (Exp)	17 modal strain energy samples (Exp), 44 samples (FE)	Damage localization from 136 structural states

4 CONCLUSIONS

In this paper, a systematic overview of vibration-based deep learning techniques in structures is provided, several conclusions can be drawn as follows.

Deep learning methods based on CNN have great potential for detecting structural damage to bridges. An important factor in determining the detection accuracy is the quality of the data set formed by the vibration response signal. A large capacity and high-fidelity data set are prerequisites for the successful application of this method in bridge structures.

The combination of vibration test and numerical model is an advanced method. The numerical model can be updated using modal parameter identification with the measured data from real structures. It can greatly improve the fidelity of the generated dataset from numerical models. To this end, the SHM sensor network of the bridge can provide vibration response data sets under different environments and vehicle excitation, which will greatly improve the robustness of the depth learning model to environmental and other impacts when conducting damage identification.

In conclusions, it is a low-cost and efficient way to update the high-fidelity numerical model based on the measured data of its sensor network and generate a large sample size damage dataset to train the deep learning model, which should be a future trend of bridge SHM.

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