Original Article

Structural Health Monitoring
2024, Vol. 23(4) 2221–2237

DOI: 10.1177/14759217231200096
journals.sagepub.com/home/shm
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Bridge anomaly detection based on reconstruction error and structural similarity of unsupervised convolutional auto-encoder

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Abstract

This study presents a novel bridge anomaly detection approach that employs the reconstruction error and structural similarity of an unsupervised convolutional auto-encoder. The presence of structural damage in a bridge typically results in changes in its vibration signals, and thus, the use of these signals for structural damage detection (SDD) has been widely investigated, with many methods relying on supervised learning. However, such existing SDD methods based on the supervised learning require prior knowledge of the damage states and cannot process monitoring data in real-time, thereby limiting their application to in-service bridges. To address this challenge, the authors propose the use of a convolutional auto-encoder as the reconstruction algorithm for real-time vibration signals. The auto-encoder is trained using normal signals and then used to reconstruct new inputs (either normal or abnormal). Two damage indicators (reconstruction error and structural similarity) are then calculated based on the reconstruction results and clustered to detect abnormal signals. The proposed approach was applied to the detection of various abnormalities in the old ADA Bridge, the results were 100% accurate, and about a 10% increase in accuracy was observed when compared to other control experiments. These results demonstrate the effectiveness of the proposed approach, with the auto-encoder achieving excellent reconstruction results for normal signals and clear discrepancies for abnormal signals. The proposed method was also validated on a cable-stayed bridge and an arch bridge, demonstrating its wide applicability in bridge anomaly detection.

Keywords

Bridge anomaly detection, unsupervised learning, convolutional auto-encoder, reconstruction error, structural similarity

Introduction

Structural damage detection (SDD) is an important means to ensure the normal operation of bridges.[1] Due to the influence of various environmental factors such as oversized vehicles and bad weather,[2] etc., some defects are inevitably accumulated in the in-service bridge structures,[3] the normal operation of the bridge structures is affected by these potential damages, and the sudden collapse of a bridge will cause significant personnel and property losses.[4] In order to prevent catastrophic failure and prolong the service life of bridge structures, an appropriate SDD technique must be utilized to detect potential damage at an early stage. In the early days, the SDD is carried out in some long-span bridges by inspectors through visual inspections on site.[5] However, this method is inefficient and lacks satisfactory detection accuracy. Then a series of vibration-based damage detection methods have been developed and become popular,[6,7] and their effectiveness has been validated in the numerical models[8] or on real structures.[9] Some advanced filters are also employed to

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analyze vibration signals for damage detection.[10] With the development of machine learning (ML) and deep learning (DL) techniques, these intelligent learning algorithms have been introduced in different research fields to enhance intelligence levels,[11] and their combination with the vibration-based SDD methods has made breakthrough progress.[12] This has led to a considerable improvement in detection accuracy and efficiency.

The ML and DL-based SDD methods typically fall into two classical types: supervised and unsupervised. The supervised SDD methods require both the normal data from normal scenario and abnormal data of various damage scenarios of the detected structure in order to implement damage detection tasks.[13,14] However, it is essentially difficult to obtain sufficient damage scenarios from the in-service civil structures. Most damage detection tasks rely on the finite element or laboratory models.[15,16] One study implements damage detection of a simply-supported beam through the supervised convolutional neural network (CNN);[17] the results confirm the excellent performance of the CNN and also demonstrate its damage feature extraction process. The damage detection task of a numerical steel frame model is also realized through the supervised CNN;[18] it is confirmed that the combination of the modal strain energy and vibration signals can significantly improve the accuracy of damage detection. Teng et al.[19] also demonstrate the excellent performance of the supervised learning in a long steel frame structure in the laboratory. And some studies are based on vibration tests of old bridges before their demolition or rehabilitation, for example, the old ADA Bridge (Japan)[20] and KW51 bridge (Belgium).[21] Although real bridge structures have been used for damage detection, the proposed damage scenarios are still a priori (the existence of damage is known in advance), the training of ML or DL needs the data of damaged scenarios. However, the potential damage scenarios of a bridge structure in service are unknown. Therefore, the damage detection based on supervised SDD methods for the in-service structures is still a challenging task.[22]

The unsupervised SDD method can effectively overcome the need for the abnormal data of structural damage scenarios. The unsupervised SDD method only needs the normal data from intact scenario of the bridge structure and does not need to label training samples.[23] Figueiredo et al.[24] employ four ML algorithms to detect damage scenarios in a frame structure, in which the autoregressive (AR) parameters are considered as the damage features. Entezami et al.[25] propose an innovative residual-based feature extraction method to extract the AR parameters from the structural vibration signals to detect damages. Sarmadi and Karamodin[26] propose a new algorithm based on adaptive Markov square distance and one-class K-nearest neighbors (KNNs) for SDD under environmental effects. In addition, the clustering analysis of various unlabeled training data has been widely used in the SDD field. For example, Cha and Wang[27] propose a fast clustering algorithm based on density peaks for structural damage localization, and achieving satisfactory damage localization results. Diez et al.[28] propose an unsupervised SDD method using the K-means algorithm to detect the bridge damages. Recently, the one-class support vector machine (OC-SVM), which is a branch of support vector machine (SVM), is also used for the unsupervised SDD,[29] and an excellent detection performance has been achieved, and as a classical unsupervised learning method, the auto-encoder has also achieved excellent results in the field of active noise control[30] and bridge anomaly detection.[13] In order to detect structural damage in the form of bolt looseness in steel bridges, Wang and Cha[31] selected four ML methods (namely KNN method, Gaussian Mixture model, OC-SVM, fast clustering method based on density peak) and a deep auto-encoder, the fast clustering method based on density peak achieved the best performance in terms of damage localization in comparison with the other methods. Meanwhile, the author also points out that the deep auto-encoder can automatically extract damage features, providing a potential solution for unsupervised damage detection.

According to the literature review, the DL technique represented by the supervised CNN has made a breakthrough in the field of SDD; it can achieve the detection tasks of low-level and high-level damage scenarios.[4] Based on this, this paper will provide a new solution to the current challenges from the following aspects:

(1) Due to its particular operation mechanism, including partial connection and weight sharing,[32] the CNN also has excellent performance in detection efficiency, which can solve the current challenge of low detection efficiency of unsupervised learning. Therefore, this paper introduces a CNN-based auto-encoder to carry out the SDD task in an unsupervised manner, that is, the convolutional auto-encoder is used to reconstruct the real-time vibration signals.
(2) In order to improve the detection accuracy, two damage indicators, the reconstruction error and structural similarity are used to evaluate the reconstruction results, in particular, the structural similarity indicator is first introduced into the evaluation of vibration signals as a novel contribution, finally, their combination is proposed to accomplish the abnormal bridge detection task.

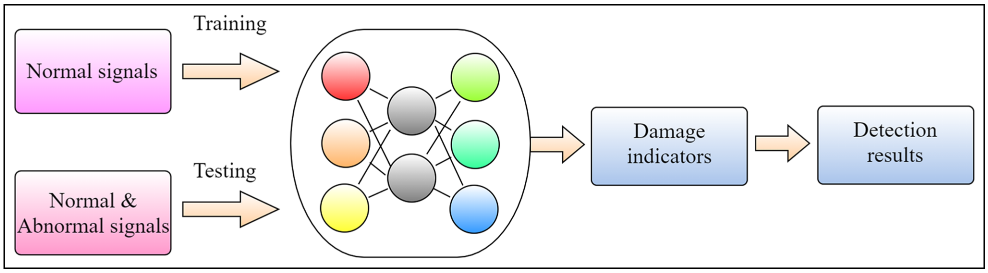

Figure 1. Implementation process of the proposed method.

Figure 2. The old ADA Bridge.

Methods

In this paper, a convolutional auto-encoder was trained by the normal bridge vibration signals, and then was used for the reconstruction of the new input vibration signals (i.e., the testing process, including normal and abnormal scenarios). According to the reconstruction results, the two damage indicators were calculated, and the normal and abnormal scenarios were detected through these two damage indicators. The specific implementation process was shown in Figure 1. The proposed method was applied to three real bridges (a steel truss one, a cable-stayed one and an arch bridge one) to validate the applicability of the proposed method.

Bridge description and damage scenarios

The old ADA Bridge used in this paper was located in Nara Prefecture, Japan (34°21′42.5″N and 1n°44′ 56.0″E). As shown in Figure 2, the bridge was a simply supported steel truss with a main span of 59.2 m and a width of 3.6 m. The detailed structural dimensions were seen in a data paper published in the Journal of bridge engineering.[20] The damage locations of the bridge and the layout of accelerometers were shown in Figure 3. During the experiment, the bridge was excited through a vehicle (with different running speeds), and its acceleration signals were collected. As shown in Figures 3 and 7, five structural scenarios were included: one intact scenario (INT), three damage scenarios (DMG1, DMG2, DMG3) and one recovery scenario (RCV). The damage locations of DMG1, DMG2, and RCV were the same, but the types of damage were different. Please refer to section “Data setup and training” for specific damage descriptions.

Convolutional auto-encoder

The auto-encoder was an unsupervised learning method. Its training was to minimize the reconstruction error between its input and output through learning important latent feature in the samples.[33] In an auto-encoder, a pair of encoder and decoder structures was used to create an output that was close to its original input and the optimization target was to perfectly reconstruct the input. The input data was compressed by the encoder to obtain its low dimensional features, which were reconstructed by the decoder to obtain the features consistent with the original data.

The classical artificial neural network (ANN) model was used as the encoder and decoder of a traditional

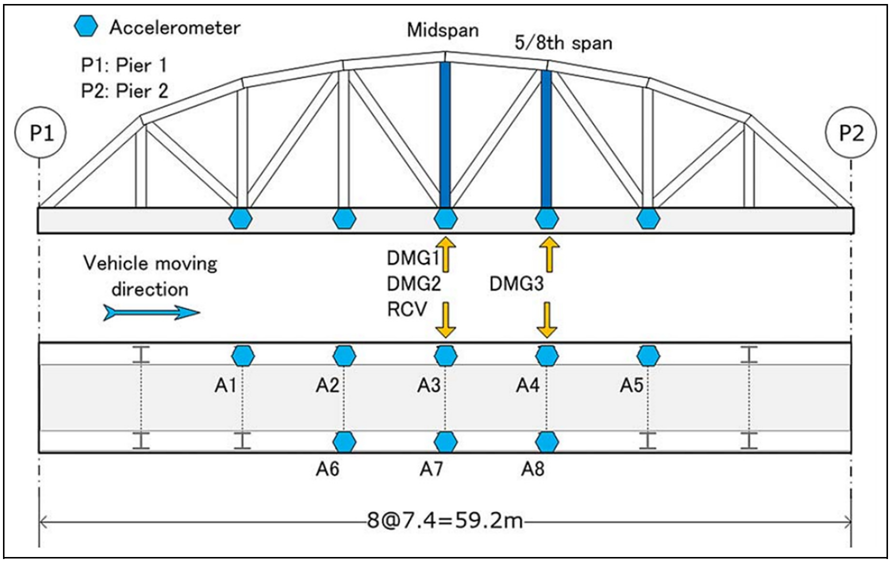

Figure 3. The damage locations of the bridge and layout of accelerometers.

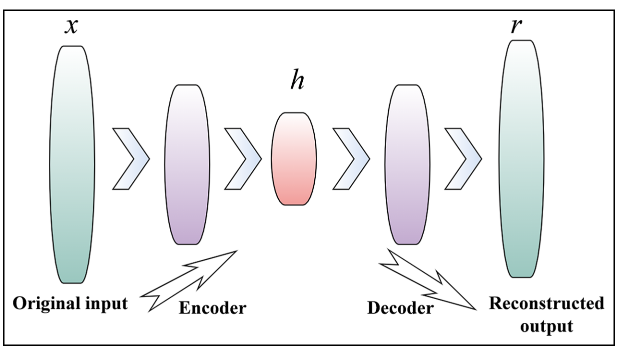

Figure 4. The framework of auto-encoder.

auto-encoder (Figure 4). As a substitute for ANN, the CNN has recently achieved outstanding performance in the field of SDD. Therefore, this paper introduced a novel convolutional auto-encoder, in which the CNN was used to extract and represent data features. Firstly, the encoder encoded the input data and maps its features to the hidden layer space (which was expressed by the coding function $h = f(x)$), and then the decoder decoded the features of the hidden layer space (the process of reconstruction) to obtain the reconstructed samples (which was expressed by the decoding function $r = g(h)$).

A convolutional auto-encoder was established based on MATLAB platform (MathWorks Inc, Natick, MA, USA) in this paper, including a sequence input layer, two convolution layers and two transposed convolution layers (each of them followed by an activation layer), a fully connected layer and a regression output layer (Figure 5). The regression layer can output the reconstructed signals of the original ones through the convolutional auto-encoder. The two convolution layers were used as the encoder to extract the feature information of the original signals, and the two transposed convolution layers were used as the decoder to reconstruct the original input data; that is, the convolution and transposed convolution processes were two opposite operations, which represented data compression and data restoration. The detailed operation process is described below in detail.

A convolution process (Figure 6(a)) was to multiply each element in the convolution kernel with the corresponding element in a sub-region (e.g., Green box, Red dotted box) of the original data of the convolution layer and sum up the products to obtain an element in the feature map. Each time, the sub-region moves down one step and the process was repeated until all elements of the original data were involved; in the end, the convolution operation will form a new array (i.e., the feature map).

Transposed convolution was an up-sampling process (Figure 6(b)). Firstly, the original data increased the geometric size of the data by filling the boundary. The subsequent operation process was similar to the classical convolution operation, that is, the feature data array was obtained as the convolution kernel slid in the filled data. The geometric size of this array was larger than that of the raw data, that is, the up-sampling process of the data was completed.

Data setup and training

The dataset used in this paper was the benchmark data set of the real bridge described in section "Bridge

Figure 5. The proposed convolutional auto-encoder.

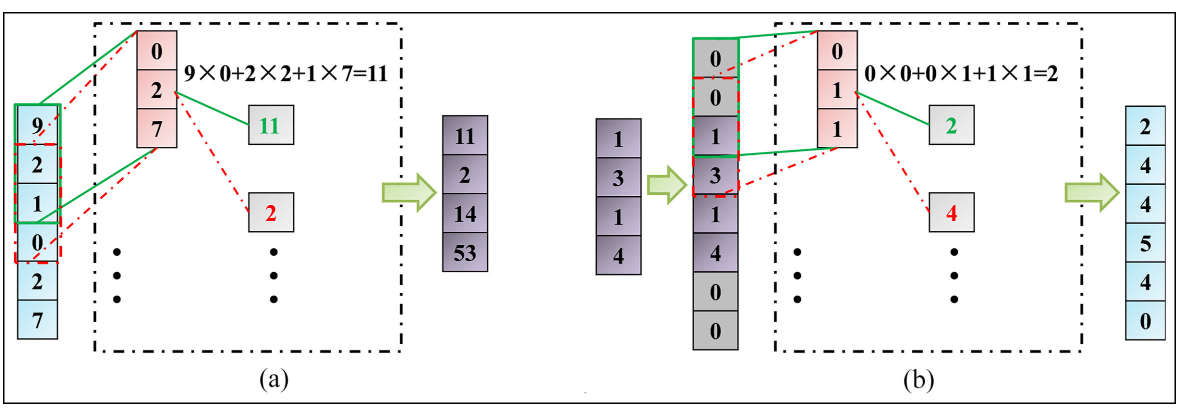

Figure 6. The convolution and transposed convolution processes. (a) Convolution, and (b) transposed convolution.

description and damage scenarios." The bridge underwent a series of vibration experiments before demolition. Five structural scenarios (Figure 7) were implemented, namely one intact structural scenario, and four bridge damage scenarios were intentionally generated.

Scenario S1: Intact scenario (three bridge vibration experiments with different vehicle speeds were tested);
Scenario S2 (DMG1): The damage occurred on a vertical truss member of the mid-span (half of the section was cut off);
Scenario S3 (DMG2): The vertical truss member of the mid-span was completely cut off;
Scenario S4 (RCV): The vertical truss member of the middle span was repaired (it cannot be completely restored to the original intact scenario);
Scenario S5 (DMG3): The vertical truss member of the 5/8th span was completely cut off.

In this paper, the acceleration signals caused by the vehicle loads in the various scenarios were employed. The layouts of eight accelerometers were shown in Figure 3. For the acceleration signals (e.g., intact

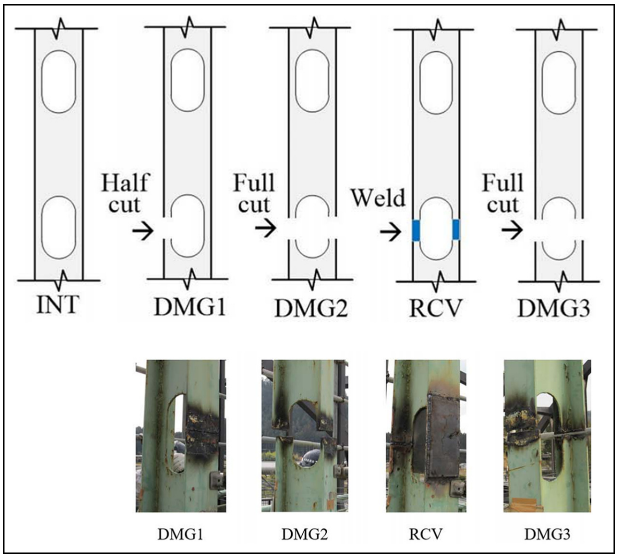

Figure 7. The damage scenarios of the employed bridge.

structure, vehicle speed: 40 km/h) of each sensor, a total of 35 s with the sampling frequency of 200 Hz were recorded, as shown in Figure 8, thus acceleration signals at 7000 time points were collected. As the acceleration signals at every 100 time points was used as a sample, thus 70 samples were obtained from each accelerometer and totally 560 samples were obtained for the intact structural scenario. The sample acquisition process for other damage scenarios was consistent with the above.

As an unsupervised learning algorithm, the convolutional auto-encoder did not need to label each sample. As being trained by the bridge vibration signals in the normal state (intact scenario), in the ideal effect, the convolutional auto-encoder had an excellent reconstruction effect on the normal vibration signals, but the reconstruction effect of the abnormal signals (damage scenarios) of the bridge vibration was not ideal.

At the same vehicle speed (40 km/h), the vibration signals of the intact bridge (normal signals) and damaged bridge (abnormal signals) were detected. This experiment was also carried out five times in total. Detailed training and testing samples of each experiment were shown in Table 1.

Performance evaluation and scenario classification

In this paper, two performance indicators were used to evaluate the effect of vibration signal reconstruction. (1) Error, which has been applied to relevant researches,[13,29] the sum of the reconstruction errors of the eight accelerometer channels was used to evaluate the absolute error of the original vibration signals (input signals) and the reconstructed signals (output signals), the closer the error was to 0, the better the reconstruction effect was; (2) Structural similarity (SSIM), which calculated the similarity between the original vibration signals (input signals) and the reconstructed signals (output signals), the closer the similarity was to 1, the more similar to each other the two signals were. The similarity was usually applied to the spatial similarity of a pair of images;[34] in this paper, it was introduced to evaluate the reconstruction effect of vibration signals, which could realize the measurement of shape similarity of vibration signals.

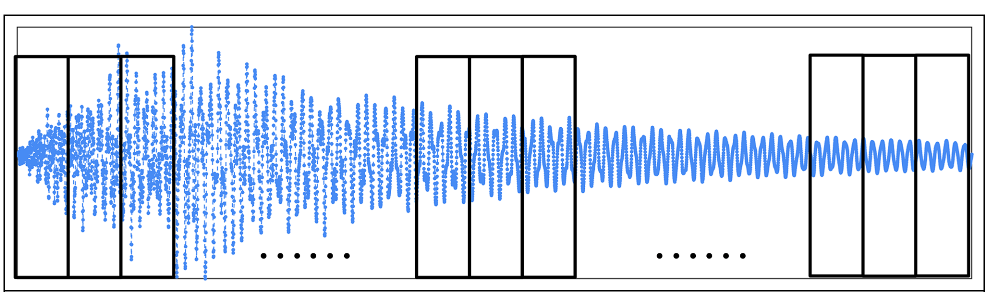

Figure 8. Sample acquisition method.

Table 1. The training and testing samples (bridge damage scenarios).

Sample type	Normal signals (intact structure)	Abnormal signals			
		DMG1	DMG2	RCV	DMG3
Training	20 s (320 samples)	None	None	None	None
Testing	15 s (240 samples)	15 s (240 samples)	15 s (240 samples)	15 s (240 samples)	15 s (240 samples)
Total	35 s (560 samples)	15 s (240 samples)	15 s (240 samples)	15 s (240 samples)	15 s (240 samples)

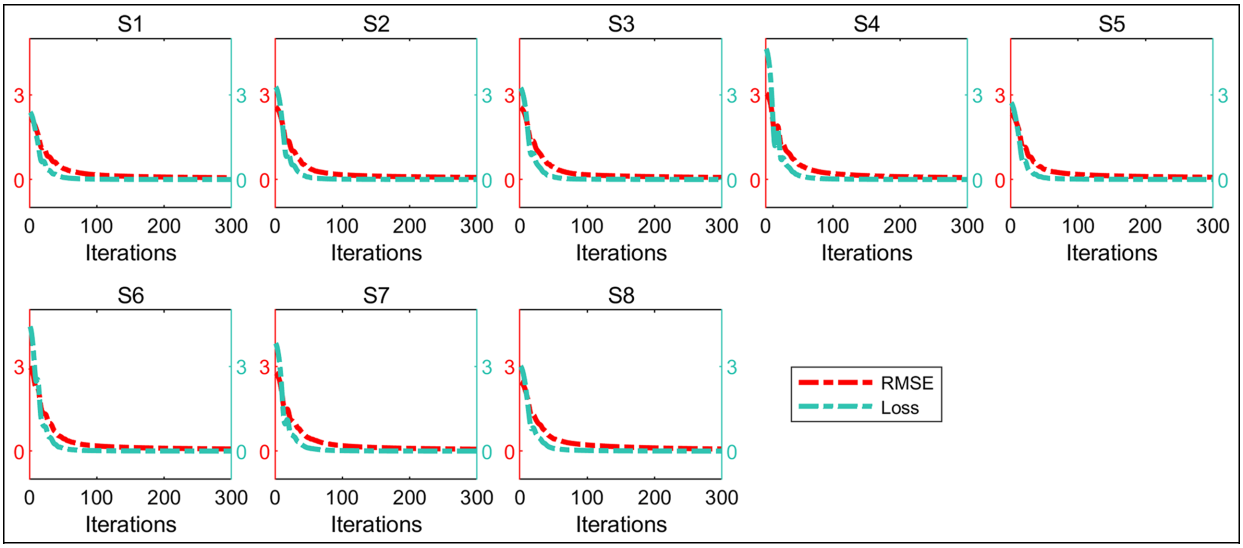

Figure 9. The training processes of different sensors.

$$\text{SError} = \sum_{m=1}^{M} |I_{\text{m}} - J_{\text{m}}| \quad (1)$$

$$\text{Error} = \sum_{n=1}^{N} \text{SError}_{\text{n}} \quad (2)$$

where, I and J are the predicted and real values of the convolutional auto-encoder respectively. M is the number of testing samples, and SError is the error of the signals of one accelerometer. N is the number of accelerometers, and Error is the error of the signals of all accelerometers.

$$\text{SSIM}(I, J) = \frac{(2\mu_{\text{I}}\mu_{\text{J}} + C_1)(2\sigma_{\text{IJ}} + C_2)}{(\mu_{\text{I}}^2 + \mu_{\text{J}}^2 + C_1)(\sigma_{\text{I}}^2 + \sigma_{\text{J}}^2 + C_2)} \quad (3)$$

Where, μ_{I} and μ_{J} are the local means of I and J, respectively; σ_{I} and σ_{J} are the standard deviations of I and J, respectively; and σ_{IJ} is the cross covariance of I and J; C_1 and C_2 are 6.5 and 58.5 respectively.

In this paper, the extreme value distribution theory was employed to estimate the threshold of the results obtained from the evaluation indicators and calculate the threshold of abnormal data. The specific operation: the "fitdist" function in MATLAB was used to fit the evaluation indicators to the "Weibull" extreme value distribution, and the "icdt" function was used to calculate the threshold of abnormal data based on the fitted extreme value distribution. Then, the two indicators were used for the detection of structural scenarios. As an innovative contribution of this paper, two evaluation indicators were used to draw the scatter plot and classify each sample according to its location distribution in the scatter plot. Ideally, the data from different scenarios will be gathered at different locations. This paper will detect the abnormal scenarios according to the Error-SSIM scatter plot.

Results and discussions

This section includes four parts: (1) Abnormal detection of bridge damage; (2) Comparison with other auto-encoders; (3) Validation of the proposed method on a cable-stayed bridge and an arch bridge. The applicability of the proposed method was confirmed by the validation research on different types of bridges. The specific results were as follows:

Abnormal detection of bridge damage

The training dataset (intact scenario, Scenario S1) obtained in section "Data setup and training" was used to train the convolutional auto-encoder. The training processes of eight accelerometers were shown in Figure 9. These convolutional auto-encoders reached the convergence state after about 50 iterations and maintained a small root mean squared error (RMSE) and loss values. Then the testing dataset (damage scenarios) were used to evaluate the performance of the trained convolutional auto-encoder. The testing results of 150 testing samples were shown in Figure 10. Samples 1–30 belonged to Scenario S1, Samples 31–60 to Scenario S2, Samples 61–90 to Scenario S3, Samples 91–120 to Scenario S4, and Samples 121–150 to Scenario S5. For the testing samples in Scenario S1, the reconstruction error was small and the structural similarity was high, which indicated that the convolutional auto-encoder trained in Scenario S1 had excellent reconstruction effect on the testing dataset of Scenario S1, while for the samples in Scenario S2, Scenario S3, Scenario S4, and Scenario S5, the

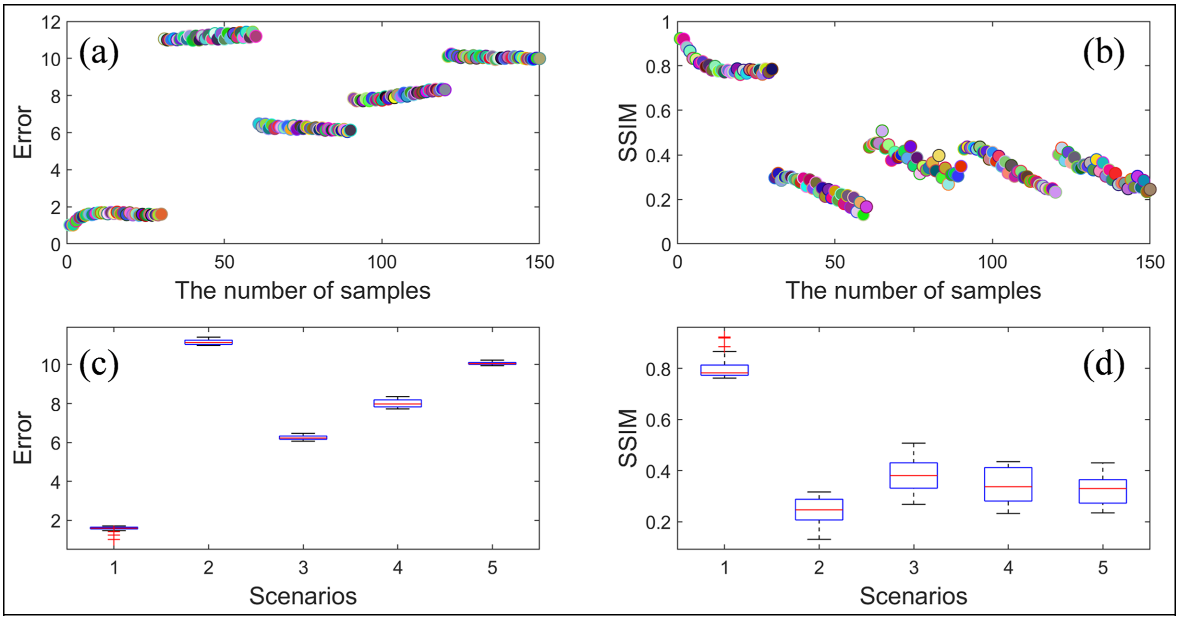

Figure 10. Testing effect of two evaluation indicators. (a) The error of all samples, (b) the SSIM of all samples, (c) the error distribution of samples in different scenarios, and (d) the SSIM distribution of samples in different scenarios.

reconstruction effect was poor (with high reconstruction error and low structural similarity). Some reconstruction examples were shown in Figure 11; Figure 11(a) and (b) showed the reconstruction effect of normal scenarios, Figure 11(c) and (d) showed the reconstruction effect of the abnormal scenarios. The results showed that the reconstruction effect of the intact scenario was ideal, but the reconstruction effect of the damage scenarios was not satisfactory.

Then, the normal and abnormal samples were classified by different thresholds. Figure 12 showed the classification accuracy of the error and structural similarity threshold. For Figure 12(a), when the error threshold was between 1.72 and 5.95, 100% classification accuracy was obtained, which meant that the vibration signals was abnormal once the reconstruction error exceeds 5.95; the reconstruction error was less than 1.72, which means that the signal was normal; for Figure 12(b), when the structural similarity error was between 0.52 and 0.76, 100% classification accuracy was obtained, it meant that the signal was abnormal once the structural similarity was lower than 0.52; the structural similarity was higher than 0.76, which means that the signal was normal. The above results were based on prior knowledge to determine the threshold range. However, in order to achieve unsupervised damage detection tasks, the extreme value distribution theory was used to automatically estimate the threshold. The thresholds of error and structural similarity were 3.6 and 0.58, respectively, which belong to the prior threshold range. Therefore, 100% detection accuracy can be achieved through the unsupervised damage detection method. Therefore, the state of the vibration signals (normal or abnormal) can be accurately judged by observing the error and structural similarity between the reconstructed signals and the real-time input ones. It provides a reliable early warning mechanism for the real-time operation states of the bridge structures, that is, once the evaluation indicator exceeds the threshold range, it means that there was a potential abnormal signal, indicating that the bridge may be damaged and reminding managers to pay attention to the changes of the bridge structures.

The results of the five experiments were shown in Table 2. The error range of reconstruction was between 1 and 6, and the average threshold obtained through the extreme value distribution theory was 3.1, within which the average accuracy was 100%. Similarly, the structural similarity of the five experiments ranged from 0.5 to 0.9, the average threshold obtained through the extreme value distribution theory was 0.72, within which the average detection accuracy was 100%. This confirms that obtaining thresholds through the extreme value distribution theory can accurately classify normal and abnormal bridge scenarios.

Then, the scatter plots were also drawn through the Error and SSIM evaluation indicators to visualize the detection results. Figure 13 showed the clustering results of the scatter plots of abnormal detection. There was an evident distance between the data of the damage scenarios and that of the normal scenarios, which proves that the Error-SSIM clustering has an

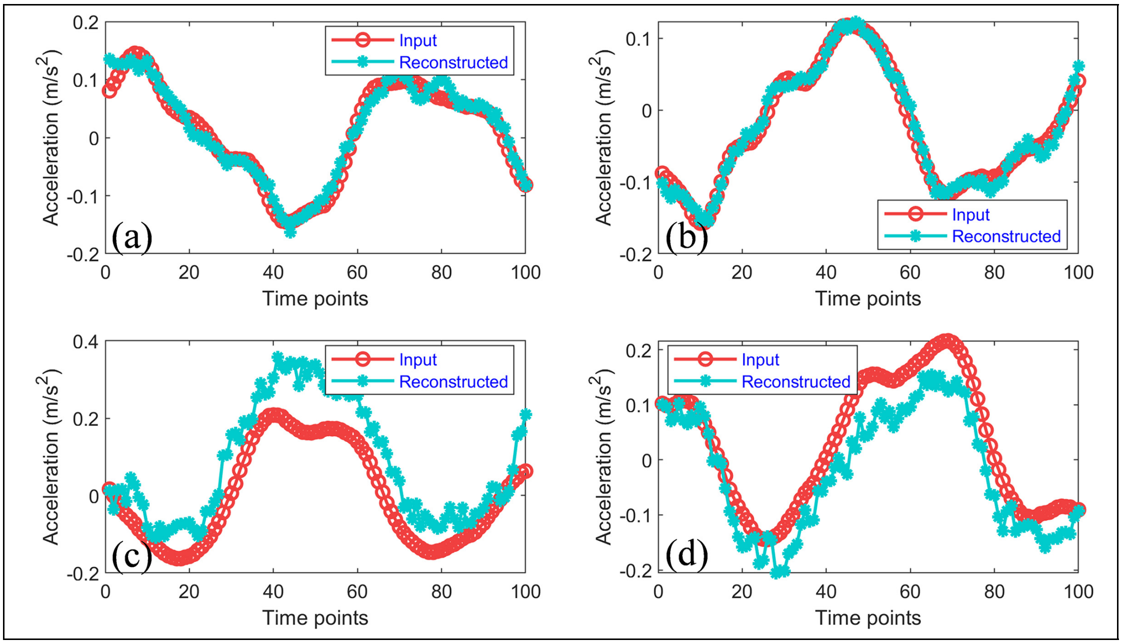

Figure 11. Reconstruction effect of normal and abnormal samples. (a) and (b) Reconstruction effect of normal scenarios, (c) and (d) reconstruction effect of abnormal scenarios.

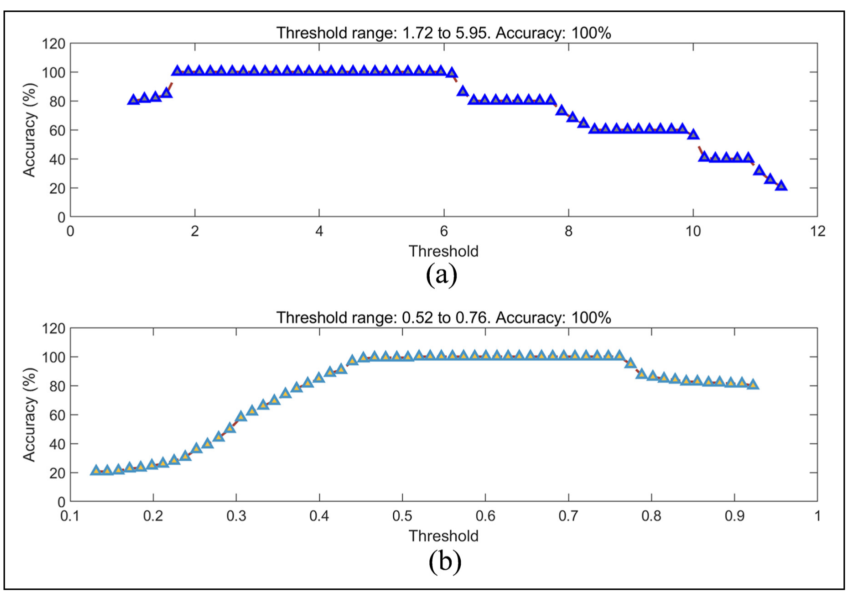

Figure 12. Detection accuracy with threshold change. (a) Detection accuracy by the error, and (b) Detection accuracy by the SSIM.

excellent detection effect on the damage and normal scenarios; although some damage scenarios were close to each other, they did not coincide with each other. They still had ideal identifications and were classified accurately, which proves that the Error-SSIM clustering can detect different abnormal scenarios. Therefore, the Error-SSIM clustering method can both detect normal and damage scenarios, and discrete different damage scenarios.

Comparative study

In order to illustrate the applicability of the proposed convolutional auto-encoder, it was further compared with other types of auto-encoders, including a LSTM (Long short-term memory network) auto-encoder and GRU (Gated recurrent unit) auto-encoder. The LSTM was a type of recurrent neural network (RNN) architecture designed to address the vanishing gradient

Table 2. Detection accuracy of threshold classification.

Number of experiments	Error			SSIM		
	Prior threshold range	Threshold estimation	Accuracy (%)	Prior threshold range	Threshold estimation	Accuracy (%)
1	1.72–5.95	3.6	100	0.52–0.76	0.71	100
2	1.73–4.8	3.2	100	0.54–0.76	0.69	100
3	1.54–4.85	3.1	100	0.6–0.8	0.71	100
4	1.46–4.48	2.9	100	0.61–0.8	0.72	100
5	1.15–3.28	2.5	100	0.71–0.84	0.78	100
Average		3.1	100		0.72	100

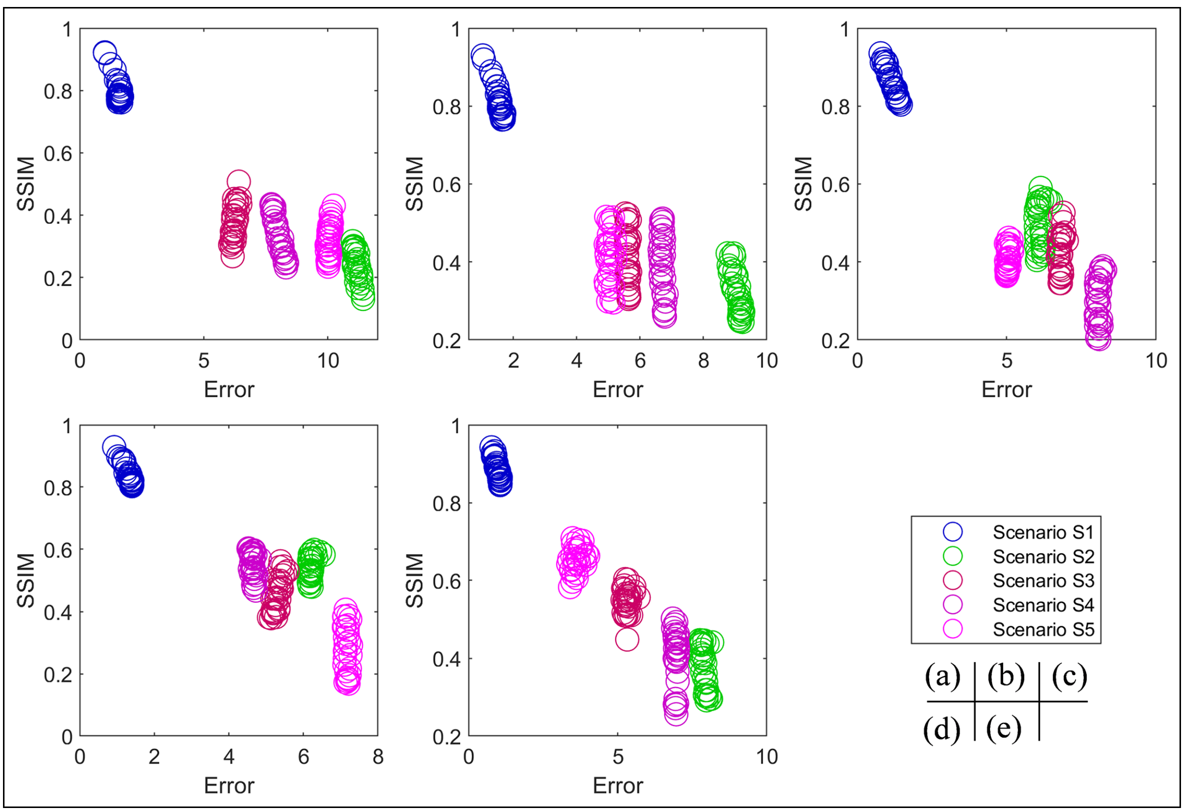

Figure 13. Clustering effect of normal and abnormal scenarios.

problem and effectively capture long-term dependencies in sequential data. It was introduced by Hochreiter and Schmidhuber in 1997. The key feature of the LSTM was its ability to retain information over long sequences, allowing it to learn and remember important patterns and relationships. The LSTM accomplishes this through the use of a memory cell, which contains three main components: an input gate, a forget gate, and an output gate. These gates control the flow of information into, out of, and within the cell, enabling the network to selectively remember or forget information at each time step. The GRU also addresses the vanishing gradient problem and captures long-term dependencies like the LSTM, but it achieves this with two main gates: an update gate and a reset gate. The update gate determines how much of the previous hidden state should be passed along to the current time step, while the reset gate controls how much of the previous hidden state should be forgotten. By adaptively updating and resetting the hidden state, the GRU can effectively model dependencies in sequential data. Compared to the LSTM, the GRU has a simpler architecture and fewer parameters, making it faster to train and requiring less memory. However, the LSTM tends to perform better on tasks that involve longer sequences and require more explicit memory management, while GRU was often favored in scenarios where computational efficiency was crucial.

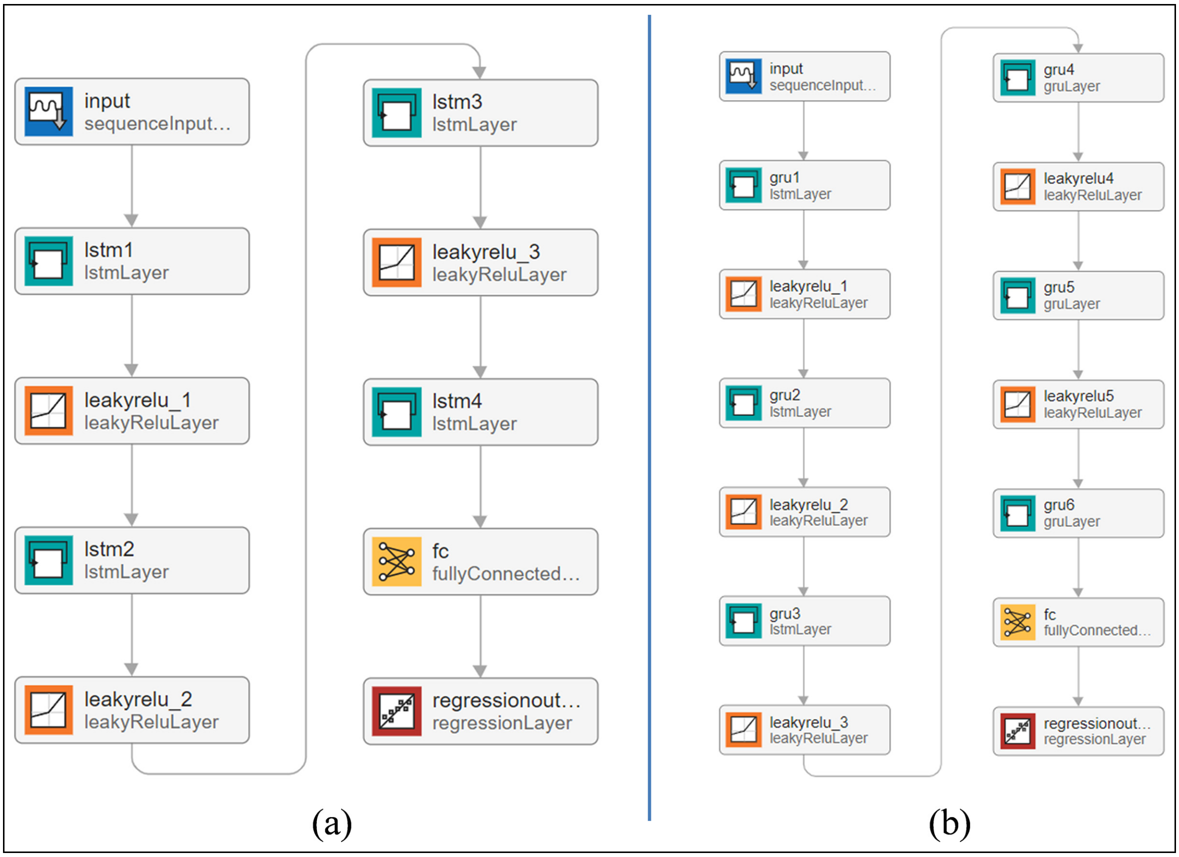

Figure 14. The optimal structures of the LSTM and GRU auto-encoders. (a) LSTM, and (b) GRU
GRU: gated recurrent unit; LSTM: long short-term memory network.

In this paper, the LSTM auto-encoder and GRU auto-encoder were built based on LSTM and GRU networks respectively. The LSTM auto-encoder was an auto-encoder model that uses LSTM networks as its encoder and decoder components. They aim to reconstruct the input data from a compressed representation called the latent space. The GRU auto-encoder was similar to the LSTM auto-encoder but uses GRU networks instead. The GRU networks were a type of RNN that has a simpler architecture compared to the LSTM while is still capable of capturing temporal dependencies. Compared to the LSTM auto-encoder, the GRU auto-encoder has a more efficient architecture with fewer parameters, making them computationally faster to train and requiring less memory. In general, they provide powerful tools for learning meaningful representations from sequential data. In this paper, the LSTM auto-encoder and GRU auto-encoder were used to reconstruct bridge vibration signals, and compared with the convolutional auto-encoder.

In order to determine the optimal hyper-parameters and training parameters of the LSTM auto-encoder and GRU auto-encoder, in this paper, the structure of LSTM and GRU auto-encoders were optimized through Bayesian optimization technology. The optimization process was shown in Appendix (Figure A1), and the error gradually decreases during the optimization process, resulting in a relatively good model structure. The optimal structures of the LSTM and GRU auto-encoders obtained through Bayesian optimization algorithm were shown in Figure 14, and these two models were employed to perform comparative tasks.

Table 3 showed the detection effect of the LSTM auto-encoder on the signals of bridge damage scenarios, compared with section "Abnormal detection of bridge damage," the results showed that the detection results of the five experiments were not ideal (the accuracy range was 80%–96%, and the average accuracy was 90.5% (Error) and 91.7% (SSIM)), and it is difficult to make a more accurate early warning decision by the inconsistent threshold range of five experiments. Table 4 shows the detection results of the GRU auto-encoder before and after bridge damage, compared with section "Abnormal detection of bridge damage," the results were still not ideal (the accuracy range was 80%–96.7%, and the average accuracy was 90% (Error) and 90.5% (SSIM)), which cannot provide a reference threshold for bridge damage detection.

Table 3. Detection accuracy of threshold classification (LSTM).

Number of tests	Error			SSIM		
	Prior threshold range	Threshold estimation	Accuracy (%)	Prior threshold range	Threshold estimation	Accuracy (%)
1	8.6–8.94	8.87	96	0.33–0.33	0.33	92
2	7.72–7.72	7.72	90	0.25–0.25	0.25	92.7
3	6.29–6.29	6.29	80	0.23–0.3	0.28	82.7
4	8.26–9.24	8.96	96	0.31–0.32	0.31	96
5	8.11–8.11	8.11	90.7	0.240.25	0.25	95.3
Average		7.99	90.5		0.28	91.7

LSTM: long short-term memory network.

Table 4. Detection accuracy of threshold classification (GRU).

Number of experiments	Error			SSIM		
	Prior threshold range	Threshold estimation	Accuracy (%)	Prior threshold range	Threshold estimation	Accuracy (%)
1	7.72–7.72	7.72	90	0.25–0.25	0.25	92.7
2	6.29–6.29	6.29	80	0.23–0.3	0.26	82.7
3	6.67–8.47	7.38	90	0.2–0.21	0.21	96.7
4	6.89–7.38	7.12	96	0.41–0.44	0.42	93.3
5	6.85–7.18	7.02	94	0.23–0.23	0.23	87.3
Average		7.11	90		0.27	90.5

GRU: gated recurrent unit.

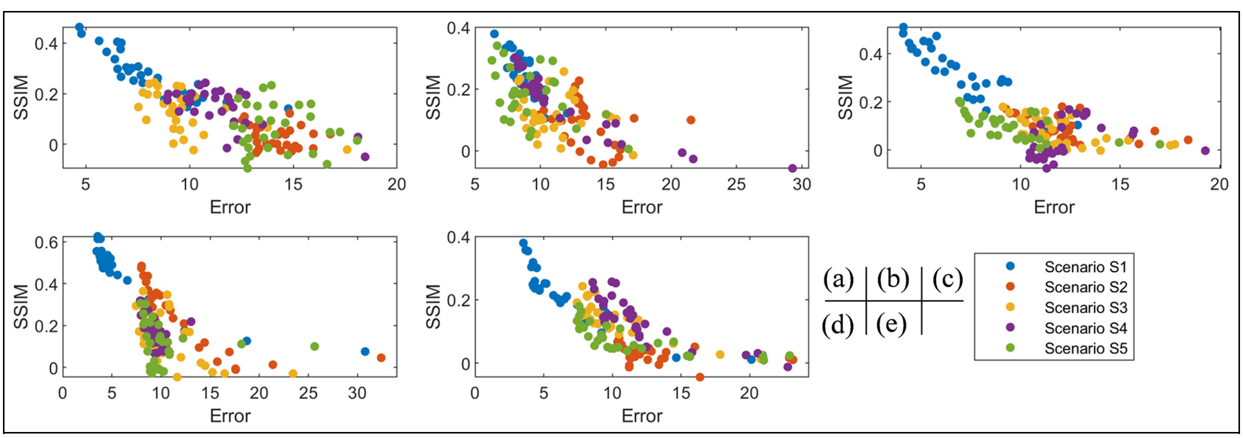

Figure 15. Clustering effect of LSTM auto-encoder.
LSTM: long short-term memory network.

Figure 15 was the scatter plots drawn by the Error and SSIM evaluation indicators to further illustrate the effect of the LSTM auto-encoder on the bridge anomaly detection. The results showed that the clustering effect of various scenarios was relatively poor, and the data of various scenarios were interwoven together, thus it was difficult to classify them. Therefore, the LSTM auto-encoder used for bridge anomaly detection was far less effective than the convolutional auto-encoder. This paper also investigated a GRU auto-encoder, and its clustering effect was shown in Figure 16, the GRU auto-encoder performed poorly too; there was no clear boundary before and after bridge damage. Therefore, it can be confirmed by comparisons that the best detection effect can be obtained through the convolutional auto-encoder.

Application in another bridge

In order to validate its applicability, the proposed method has also been applied to a cable-stayed bridge experimentally studied in the literature. The cable-stayed

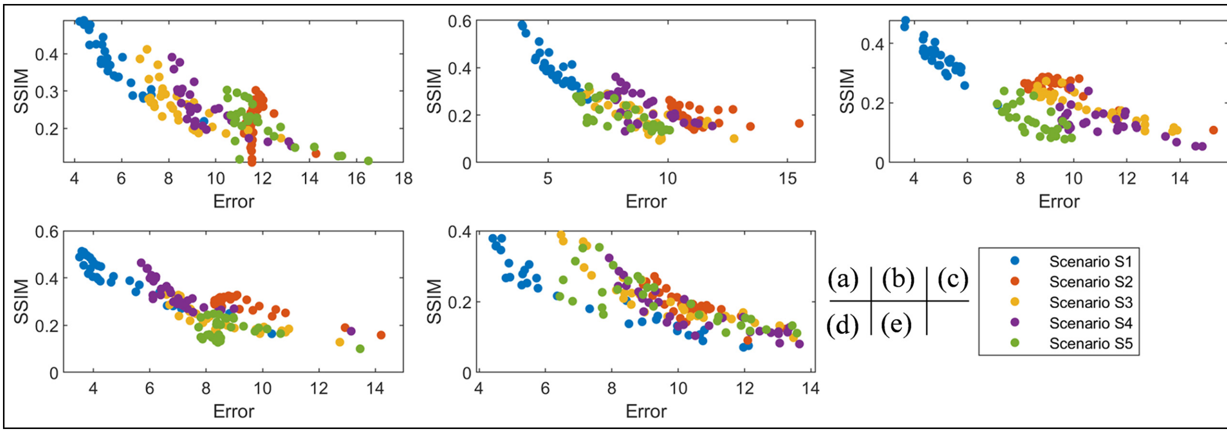

Figure 16. Clustering effect of GRU auto-encoder.
GRU: gated recurrent unit.

Figure 17. Appearance of Yonghe bridge.

bridge, Yonghe Bridge, was located in Tianjin, as shown in Figure 17. The detection team of Harbin Institute of Technology installed a structural health monitoring system on the bridge to conduct the long-term monitoring on the vibration and environment of the bridge.[35] The monitoring results showed that the natural frequencies of the bridge changed significantly from January to July 2008, the detection team claimed that the damage gradually developed during this period and vehicle control measures were implemented on 31 July 2008. Therefore, the long-term monitoring data was recognized as the benchmark time-history of the bridge from the intact to damage scenarios.

In this paper, some monitoring signals on 1 January 2008 were selected as the samples for the intact scenario, while some monitoring data on 31 July 2008 were selected as those for the damage scenario. Firstly, 50% of the intact scenario data (normal data) was used to train the convolution auto-encoder, and the remaining 50% of the intact scenario data and part of the damage scenario data (abnormal data) were used as the testing set. The reconstruction error and structural similarity of the testing set were shown in Figure 18. The reconstruction error of the normal data was small, while the structural similarity was high, and the abnormal data was opposite. Therefore, the detection of intact and damage scenarios were realized based on these damage indicators. The clustering effect of the testing set was shown in Figure 19, the results showed that different scenarios were clustered to different locations. Therefore, the clustering analysis based on two damage indicators can accurately detect the abnormal scenarios. This also confirms that the proposed method has excellent performance on the cable-stayed bridges.

This paper also carried out experimental research on the existing bridge on the Conghua Bridge, which was located in Conghua Avenue, Conghua District, Guangzhou, with a total length of 466 m, as shown in

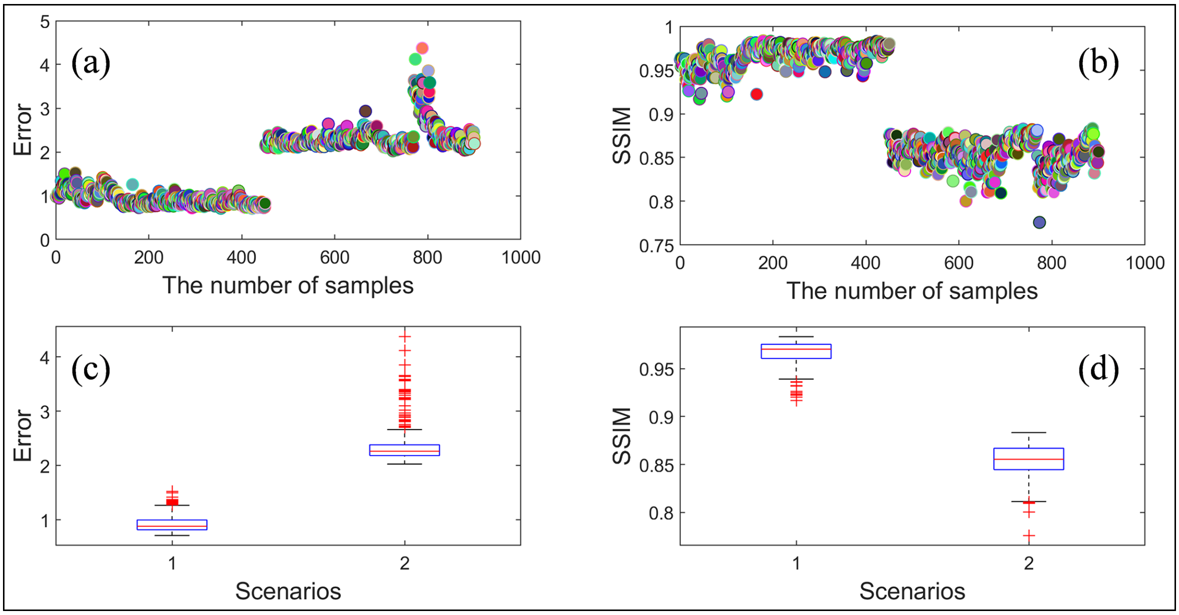

Figure 18. Testing effect of two evaluation indicators. (a) The error of all samples, (b) the SSIM of all samples, (c) the error distribution of samples in different scenarios, and (d) the SSIM distribution of samples in different scenarios.

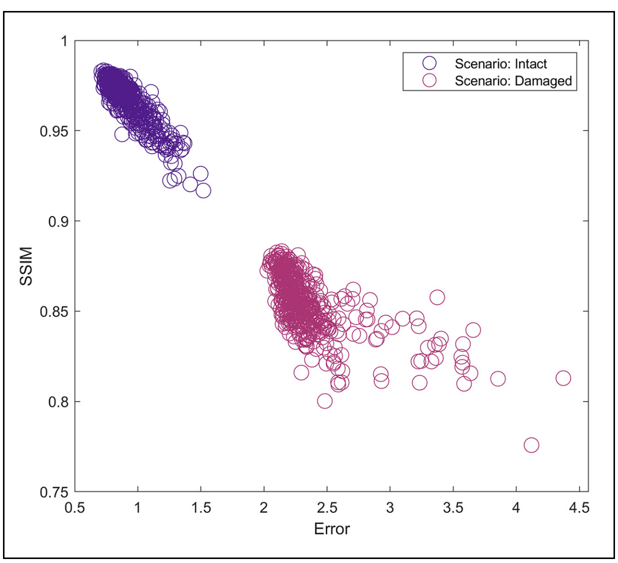

Figure 19. Clustering effect of normal and abnormal scenarios.

Figure 20. Due to the fact that the bridge was currently in service, the abnormal scenario of causing damage through human destruction was not realistic. The abnormal behavior of the bridge was created by adding counterweights to the bridge to change the dynamic characteristics of the bridge, an experimental vehicle was driven onto the bridge deck (as shown in Figure 20(c)), with a vehicle weight of approximately 3.5 tons. The vehicle was parked on the bridge deck to simulate changes in local bridge mass to create an abnormal scenario of the bridge. In this step, the traffic was not blocked and the vehicle passes normally, the driving speeds of these vehicles were inconsistent. The acceleration signal at this time was collected, and the vibration acceleration signal was collected at a sampling frequency of 100 Hz. This was used as an abnormal scenario for the bridge, and the acceleration signal collected when there were no stationary cars on the bridge deck was used as a normal scenario.

The reconstruction error and structural similarity of the testing set were shown in Figure 21. The reconstruction error of the normal data was small (the values tending toward 1), while the structural similarity was high (the values tending toward 1 too), and the abnormal data was opposite (the values of error tending toward 2.5, and the values of structural similarity tending toward 0.5). Therefore, the detection of intact and damage scenarios were realized based on these damage indicators. The clustering effect of the testing set was shown in Figure 22; the results showed that different scenarios were clustered to different locations. Therefore, the clustering analysis based on two damage indicators can accurately detect the abnormal scenarios. This also confirms that the proposed method has excellent performance on the in-service arch bridges.

Conclusions

This paper presented a novel bridge anomaly detection technique. The convolutional auto-encoder was trained by using the time-series signals in the normal scenario. Then, the new input testing signals were reconstructed by using the trained convolutional auto-encoder, and

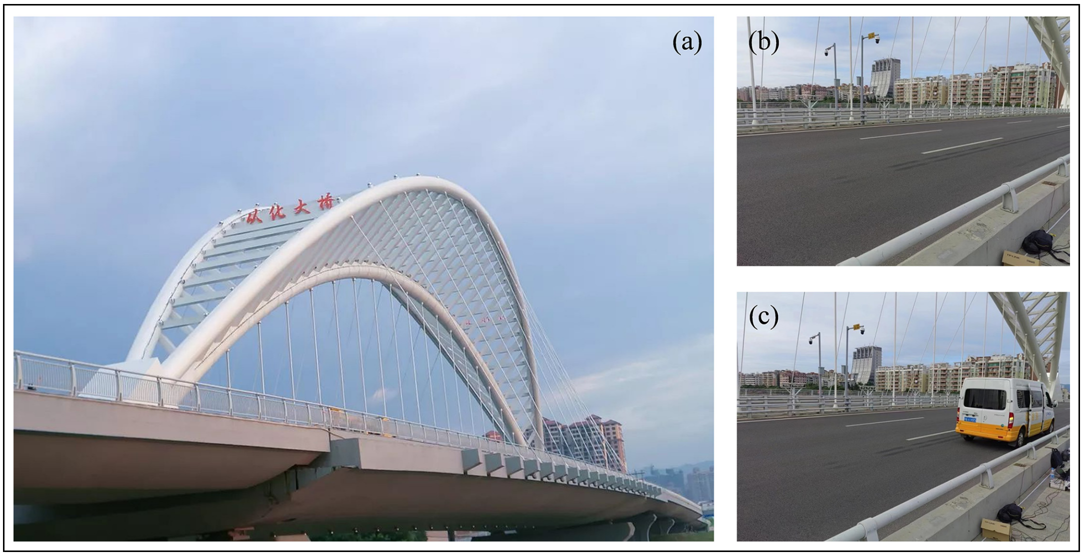

Figure 20. (a) Conghua Bridge, (b) no cars parked on the bridge deck, and (c) the car is parked on the bridge deck.

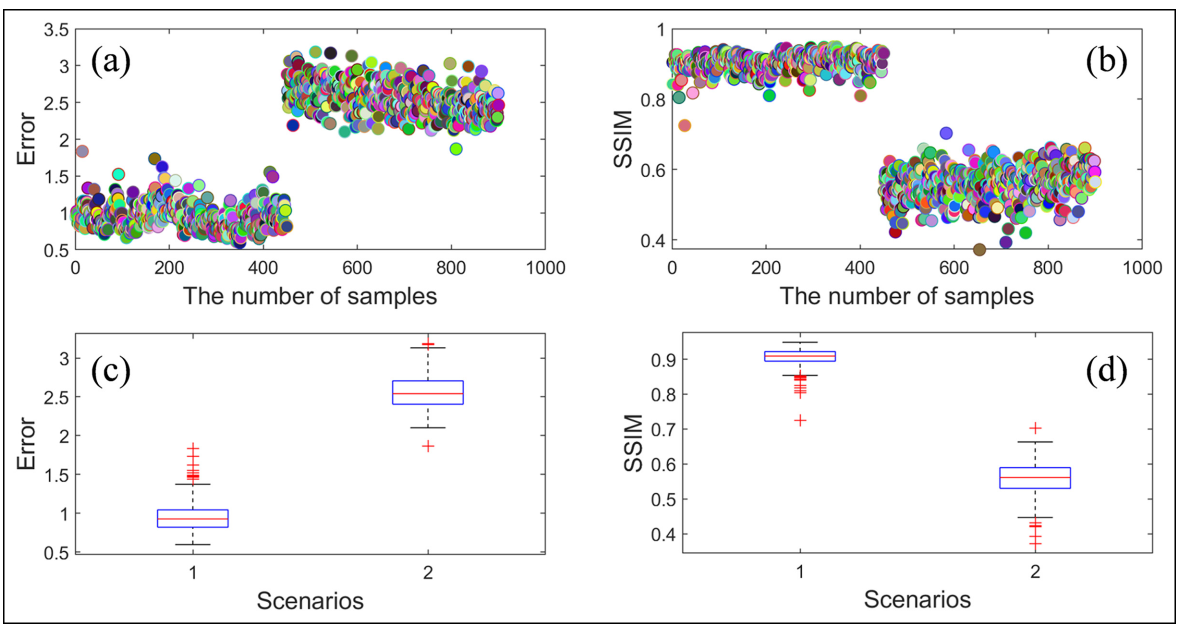

Figure 21. Testing effect of two evaluation indicators. (a) The error of all samples, (b) the SSIM of all samples, (c) the error distribution of samples in different scenarios, and (d) the SSIM distribution of samples in different scenarios.

the error and structural similarity between the reconstructed signals and original ones were calculated. These two damage indicators were used to evaluate the abnormality of the bridge. The results demonstrated that the damage indicators calculated according to the reconstruction results of the convolutional autoencoder can correctly detect the abnormal vibration signals of the bridge, and the difference between the normal and abnormal samples is clearly illustrated through the clustering diagram of the two indicators, which has important reference value for the bridge abnormal detection. Meanwhile, the effectiveness of the proposed method was validated on different types of bridges (steel truss bridge, cable-stayed bridge and arch bridge), which confirms the applicability of the unsupervised method proposed in this paper. It provides a new solution for real-time anomaly detection of bridges.

Based on the above results, the following conclusions can be drawn:

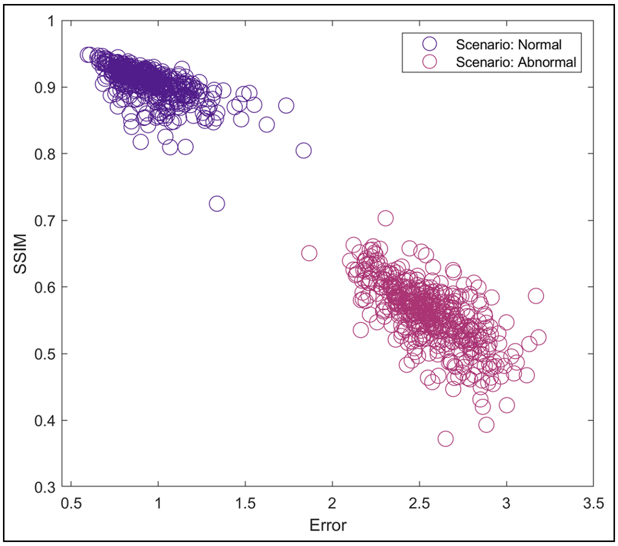

Figure 22. Clustering effect of normal and abnormal scenarios.

(1) The proposed method can also accurately detect the abnormality of the damaged bridge, with the accuracy of 100%, which is about 10% higher than that of the LSTM auto-encoder.
(2) The proposed method has excellent clustering effect, which is far better than that of other types of auto-encoders (LSTM and GRU auto-encoders). It can provide an important decision-making basis for real-time bridge inspection.
(3) The proposed method has excellent performance in the anomaly detection of different types of bridges (steel truss bridge, cable-stayed bridge and arch bridge), which confirms the significance of the proposed method.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This study was partially supported by the National Natural Science Foundation of China (Grant No. 52208309).

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Appendix

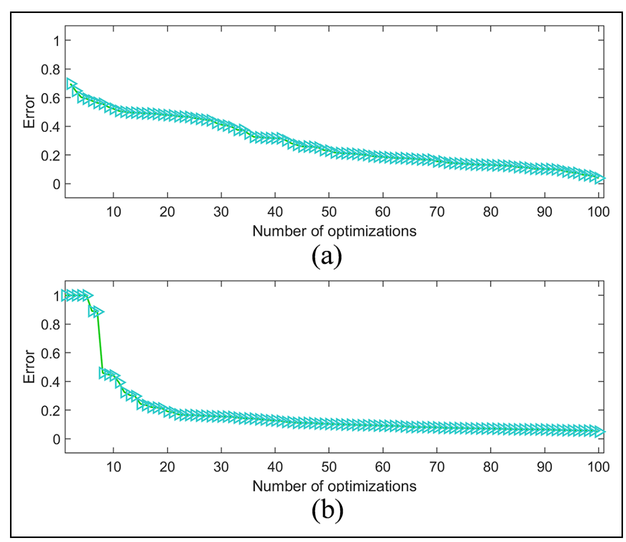

Figure A1. Bayesian optimization processes of the LSTM and GRU auto-encoders.