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Crowdsensing-based automatic bridge health condition assessment using drive-by measurements and deep learning

Zhenkun LI, Yifu LAN, Weiwei LIN
Aalto University, Espoo, Finland, zhenkun.li@aalto.fi

Abstract. In recent decades, assessing the structural health conditions of aging bridges has emerged as a significant concern. A recent drive-by measurement method has attracted substantial attention, in which only several sensors are installed on crowdsensing vehicles rather than bridges, providing a more economical and convenient solution. This paper proposes an automatic bridge condition assessment framework incorporating drive-by measurements and deep learning techniques. The methodology involves collecting and segmenting accelerations from a vehicle passing a healthy bridge into short-time overlapped frames. Over multiple vehicular passes, all frames are then transformed into frequency-domain responses, forming the input for training an unsupervised deep learning model. The model is then trained to reconstruct the input using these frequency-domain responses. In assessing the bridge with an unknown health state, the trained model is employed to reconstruct the passing vehicle's new short-time frames, and the response construction error automatically determines the bridge's health condition. Experimental validation utilizing a laboratory bridge and scaled truck demonstrated that the trained model could consistently identify a healthy bridge during passages, with larger reconstruction errors indicating that the bridge was damaged. The innovative framework showcased promise for efficient and reliable bridge health condition assessment.

Keywords: Structural health monitoring, Crowdsensing, drive-by method, automation, deep learning

1. Introduction

In recent decades, structural health monitoring (SHM) has offered valuable insights for evaluating the safety of bridge structures. Within SHM, a key focus lies in damage detection, supplying engineers with crucial information about the health status of the bridge structure [1,2]. Historically, traditional methods for assessing bridges have heavily depended on visual inspections [3], a practice that may now face limitations given the growing size of contemporary bridge constructions.

Over the past twenty years, there has been a significant rise in the monitoring of bridge health conditions through the utilization of various sensors placed on the bridge's surface or internal structure. These sensors include strain gauges, fibre optic sensors, and accelerometers [4,5]. It has been established that employing bridge vibrations for assessing its health condition shows promise in practical engineering. Nevertheless, the so-called direct method, which involves installing numerous sensors directly onto the bridge, faces limitations due to high costs and low efficiency, especially when monitoring a large number of newly constructed or deteriorating bridges [6]. As a response to these challenges, an indirect method was introduced by Yang et al. in 2004 [7]. This approach identified the fundamental frequency of a bridge from the accelerations of passing vehicles. Despite using a simplified spring-mass model to simulate the vehicle-bridge interaction (VBI), it effectively illustrated the presence of dynamic bridge information in the vibrations of passing vehicles, opening up avenues for future research on extracting bridge frequencies, modal shapes, and damping ratios [8–12]. Currently, the indirect method faces two main challenges, namely the interference of vehicle-related information in vehicle vibrations and the impact of road roughness [13]. To address the former issue, prior studies have explored the use of customized vehicles and contact-point (CP) responses [14–16]. CP responses, being independent of vehicle information, prove to be more efficient in extracting bridge-related data from vehicle responses. However, road roughness can still impede the accurate identification of bridge information. Various approaches, including utilizing residual CP responses, external amplifiers, and considering ongoing traffic, have been investigated [17–19]. Nonetheless, these methods may encounter difficulties related to measuring vehicle axle distances and the specialized design of test vehicles, indicating that challenges persist in the practical application of the indirect method.

With the advancement of computer science, data-driven methods have gained popularity across various sectors, including infrastructure health monitoring. Researchers have discovered that these techniques are particularly suitable for the indirect method due to their sensitivity to signal changes before and after bridge damage occurs. In 2019, Malekjafarian et al. [20] introduced a method for detecting bridge damage by analyzing responses from a quarter-car model. They presented two distinct approaches based on time and frequency-domain responses of vehicle responses. This initial work was later expanded to incorporate the influence of temperature variations during monitoring [21]. Subsequent studies confirmed that deep learning techniques are adept at identifying, locating, and quantifying bridge damage [22]. Other innovative investigations, such as Mel-frequency Cepstral Coefficients, deep auto-encoder, and support vector machine, have also been explored and proven to be successful [23–25]. Despite these advancements, challenges persist in practical engineering, notably regarding the availability of labelled data for damaged bridge cases. Additionally, the current methods often involve manual processes, making automation in bridge health monitoring a challenging task.

This paper presents a crowdsensing-based framework for automatically assessing the health condition of bridges using drive-by measurements and deep learning. In contrast to the traditional drive-by method, this novel approach involves multiple vehicular runs instead of just one passages. By employing crowdsensing using multiple vehicular runs instead of one drive-by vehicular run, the robustness of the proposed method to vehicle parameters and environmental noises is improved. The framework consists of four steps: 1) collect and segment accelerations from a vehicle passing over a bridge into short-time overlapped frames; 2) transform all frames into the frequency domain to obtain the vehicle’s short-time frequency responses; 3) train a deep auto-encoder to derive the damage indicator; and 4) apply the same process to assess the bridge’s health condition in real time when a new vehicle run is conducted. The remainder of the paper is organized as follows: Section 1 introduces the key steps in the proposed framework. Section 2 presents the laboratory experiment setups for the validation of the proposed method. Section 3 provides the results of bridge health condition assessment and further discussions. Finally, this paper is concluded in Section 5.

2. Proposal framework

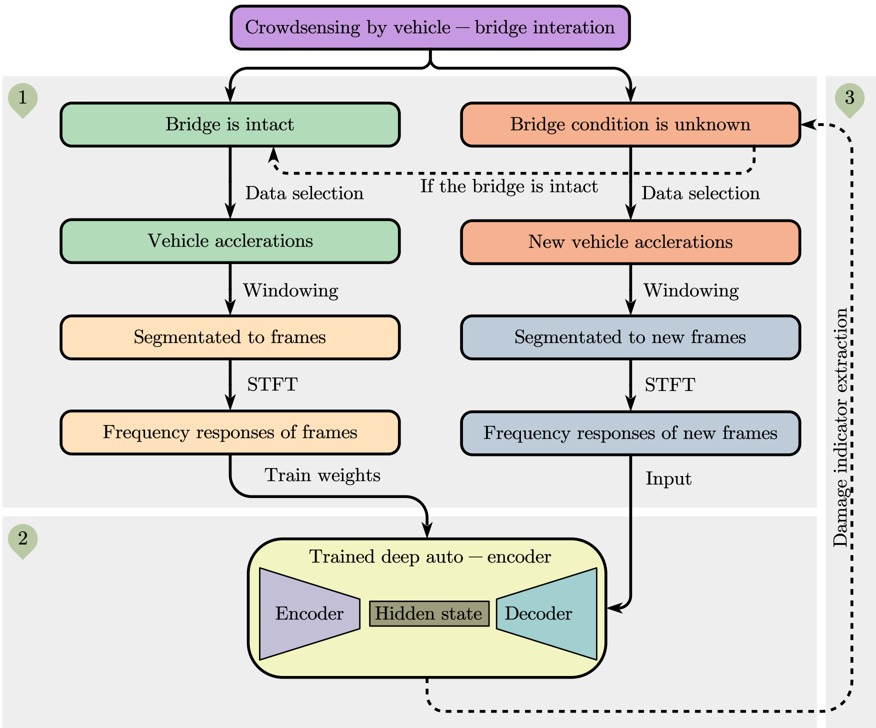

Fig. 1. Proposed framework.

2.1 Data processing

The proposed framework is illustrated in Figure 1, with the objective of assessing bridge health condition in real time. To improve the analysis results and eliminate useless information (when the vehicle is not on the bridge), vehicle accelerations are collected only when both its front and rear wheels are on the bridge. Then, the collected data are divided into frames. These frames have overlaps to ensure signal stability, and the frame length must be selected carefully, taking into account factors, e.g., the frequency of damage detection and the properties of the bridge. It is essential to find a balance between acquiring sufficient data for analysis and avoiding long analysis time. The frame length can be determined ($> T_1$) by considering the bridge's fundamental frequency (f_{b1}) and period ($T_1 = 1/f_{b1}$), with longer frames being recommended for more precise damage detection purposes.

The short-time Fourier transform (STFT) is used to obtain the frequency responses of each frame. Note that not the full-band frequency responses of each frame need to be used for analysis. Typically, the first three frequencies of a real bridge are typically within 100 Hz [10]. Therefore, only frequency responses ranging from 0 to 100 Hz can be employed. When training with X runs of a vehicle passing over an intact bridge, dividing the vibration data during the passing into frames F_i allows for the generation of a total of $M = \sum_{i=1}^{X} F_i$ frames.

2.2 Deep auto-encoder training

Auto-encoder is an unsupervised neural network that does not need labels for different samples. The auto-encoder model is used to make the outputs as similar to inputs as possible. The traditional auto-encoder consists of an encoder and a decoder, and there is one hidden layer only, which can be represented by Eqs. (1) and (2),

$$\boldsymbol{h} = f(\mathbf{W}\boldsymbol{s} + \boldsymbol{b}) \tag{1}$$

$$\hat{\boldsymbol{s}} = g(\mathbf{W}^{*}\boldsymbol{h} + \boldsymbol{b}^{*}) \tag{2}$$

where $\boldsymbol{s}$ is the input vector, $\hat{\boldsymbol{s}}$ is the output vector, $\boldsymbol{h}$ is the hidden state, f and g are activation functions, $\mathbf{W}$ and $\mathbf{W}^*$ are weight matrices, and $\boldsymbol{b}$ and $\boldsymbol{b}^*$ are bias vectors. The goal is to optimize these parameters to reduce the input-output difference.

The hidden layer in an auto-encoder holds essential input information and helps reduce input dimensions. The loss function, calculated as the error between inputs and outputs, is used to train the auto-encoder. Deep auto-encoder with multiple hidden layers can enhance the learning capability of the model. Also, in order to avoid the overfitting problem, the regularization term is utilized. Adam algorithm was used to modify the learning rate in each step. After training, the deep auto-encoder model can extract bridge vibration features from vehicle responses. However, when the bridge is damaged, the trained model will fail to reconstruct the input, making the loss increased. In this paper, vehicle frequency responses are used as input features for the deep auto-encoder to mitigate noise effects, which can enhance the model's robustness compared to using time-domain responses.

2.3 Damage indicator extraction

To detect damage, the damage indicator (DI) is calculated by comparing original and reconstructed frequency responses using a trained deep auto-encoder. For damage detection, given a frame's original frequency responses $\boldsymbol{s}$ and its reconstructed frequency responses $\hat{\boldsymbol{s}}$ using trained model, the DI can be represented by the square error as shown in Eq. (3).

$$\mathrm{DI} = \| \boldsymbol{s} - \hat{\boldsymbol{s}} \|^2 \quad (3)$$

This DI quantifies the discrepancy between healthy and damaged bridge conditions based on the reconstruction error. Lower DI values indicate a healthy bridge, while higher values suggest damage.

3. Experimental validation

3.1 Vehicle-bridge interaction model

In this section, a lab-scale model is used to test the proposed method, involving a UPE300 steel beam simulating a two-span bridge. The beam's material is Q355 with a Young's modulus of 199.0 GPa and weighs 248.64 kg. A Tamiya model truck (4.305 kg) is controlled remotely to run on the bridge (see the remote-control unit in Figure 2). Guide cables are used to ensure straight movement. As one can observe, there are patterns on the vehicle's tire and the beam's surface is smooth. Therefore, the vehicle's vibrations are mainly caused by the patterns, which can be utilized to simulate the relatively good road roughness (Class A) [22]. The bridge and vehicle models can be found in Figure 2.

Table 1. Damage cases.

Damage cases	**DC 0**	**DC 1**	**DC 2**	**DC 3**
Runs	506	49	50	42
Added mass	0 kg	5 kg	10 kg	15 kg
Damage degree	0.00%	5.63%	9.65%	13.67%

3.2 Bridge damage cases

Theoretically, once the damage occurs, the local stiffness of the bridge will reduce. As the bridge's natural frequencies are associated with structural mass and stiffness matrices, a practical way to simulate the bridge's damage is to add additional mass to the bridge [22,26]. After damage occurs in the bridge, its local stiffness decreases, affecting natural frequencies as well as frequency responses. To simulate damage, additional mass is added to the bridge in this work (see Figure 2), with different masses indicating varying damage degrees. Different damage cases (DCs) can be found in Table 1.

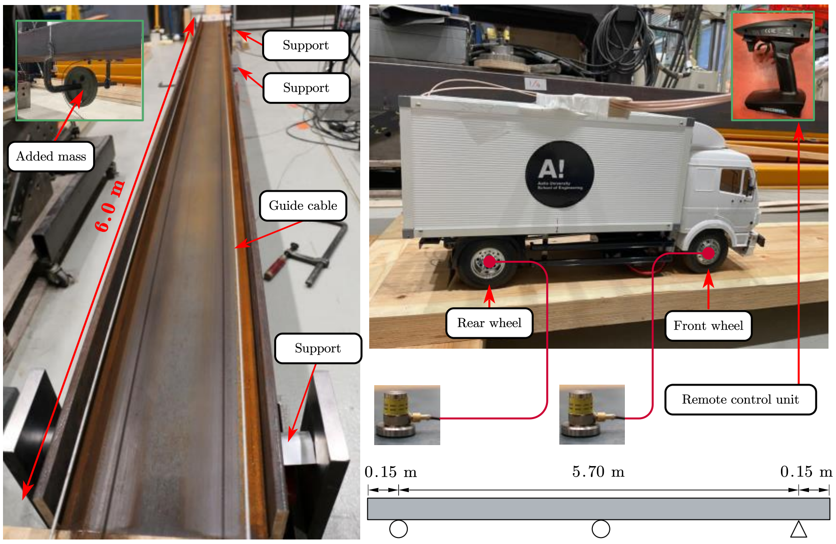

Fig. 2. Vehicle and bridge models.

4. Results and discussions

4.1 Data processing

After multiple runs on the intact bridge, data from the rear axle's vibrations are analyzed due to its heavier weight. A frame length of 1.0 s is chosen to capture ample dynamic information about the bridge for the deep auto-encoder model's effectiveness. Following preprocessing, 291170 frames of the truck's vibration data are obtained, each lasting 1.0 s. Frequency responses within 0-100 Hz are selected for damage detection to avoid computational overload. Padding zeros are used to enhance frequency response details, resulting in a resolution of 0.0763 Hz per frame.

4.2 Deep auto-encoder training

Due to the varying scales of frequency responses of passing vehicles, feature normalization is essential for enhancing the deep auto-encoder model's effectiveness. This involves adjusting the mean and standard deviation of training data, to ensure proper model generalization. The dataset is split into training, validation, and testing sets (training: validation = 9:1), with a focus on avoiding overfitting by using distinct runs for testing (401-506 runs). Training details, including optimizer and hyperparameter adjustments, are carefully managed to optimize the deep auto-encoder model's performance. The computations are carried out on a high-performance workstation at Aalto University, utilizing Python with Pytorch and sci-kit learn packages. The deep auto-encoder model is the architecture of $1310 \rightarrow 512 \rightarrow 256 \rightarrow 128 \rightarrow 256 \rightarrow 512 \rightarrow 1310$ (5 hidden layers) with 128 neurons in the bottleneck, Leaky-ReLU activation function, and L_2 regularization value of 1×10^{-5}. After training the deep auto-encoder model's model with selected hyperparameters for 1200 epochs, the loss for training, validation, and testing is displayed in Figure 3. We can see the loss is quite low, meaning that the trained model can well reconstruct frequency responses of passing vehicles on a healthy bridge within the 0-100 Hz range, with similar precision for both validation and testing data. This also indicates that the deep auto-encoder model has effectively captured the frequency response characteristics of passing vehicles on an intact bridge.

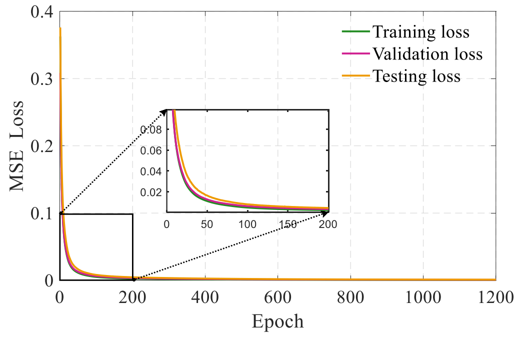

Fig. 3. Training, validation and testing loss.

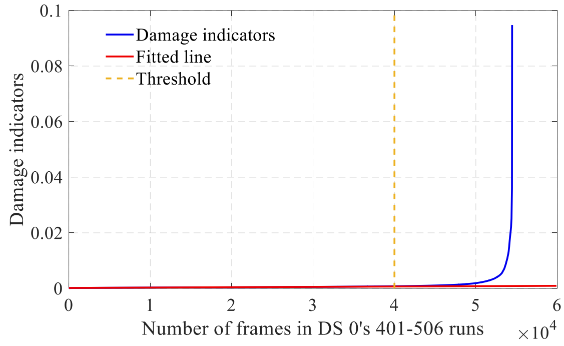

Fig. 4. Sorting DIs of 401-506 runs' frames in DC 0.

4.3 Automatic damage detection

By analyzing DIs of DC 0's 401-506 runs, we can see that most DIs are near zero, meaning that the deep auto-encoder model can reconstruct frequency responses for the healthy bridge. Also, we can see a sharp increase in DIs after the 40,000th point. A close analysis reveals that this phenomenon is caused by entering and leaving the bridge, as indicated in reference [5]. To improve real-time damage detection, outlier removal to determine the threshold is necessary. Sorting DIs in ascending order reveals a threshold value of 7.815×10^{-4} (at the 40,000th point) for health damage assessment, as shown in Figure 4.

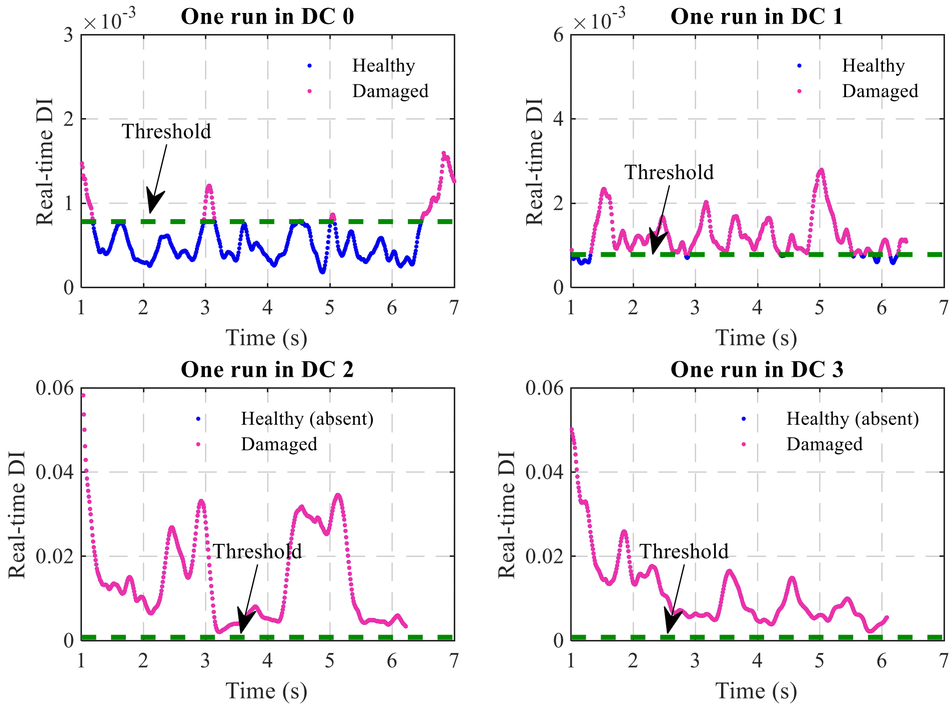

Fig. 5. Automatic damage detection results.

The results of automatic damage detection using the proposed method for a single run of different DCs are illustrated in Figure 5. Initially, in DC 0 when the bridge is intact, the system predominantly identifies the bridge as healthy (plotted by blue points) as the vehicle passes it. However, temporary inaccuracies in identification are observed at specific time intervals (e.g., 1.00-1.18s, 2.97-3.14s, 4.51-4.53s, 5.01-5.07s, and 6.48-7.00s), particularly when the vehicle enters the bridge. This can be attributed to the dynamic information collection process initiated when the vehicle begins to enter the bridge, where the available data may not be sufficient to assess the bridge's condition accurately at that moment. In cases of minor damage severity, such as DC 1, the proposed method consistently detects damage during most time of the vehicle's passage. Also, sometimes, the trained auto-encoder can also determine the bridge as healthy occasionally (e.g., 1.02-1.31s, 2.85-2.89s, 4.37-4.45s, 5.53-5.55s, 5.67-5.62s, 5.87-5.96s, 6.14-6.25s) but these erroneous determinations are quite limited. As the severity of damage increases to DCs 2 and 3, the model demonstrates improved performance in identifying the bridge as damaged throughout the vehicle's passage, with a notable reduction in inaccurate detection.

5. Conclusions and future studies

A crowdsensing-based automatic bridge health condition assessment method using drive-by measurements and deep learning is proposed in this paper. Specifically, the deep auto-encoder is employed to extract damage-sensitive features from the vehicle's responses in real-time without manual operations. Laboratory experiments with a scaled vehicle and a U-shaped beam were employed to verify the proposed method, some concluding remarks can be drawn below:

1) Short-time vibrations of the crowdsensing vehicle include the bridge's dynamic information and thus can be utilized for bridge health condition assessment.
2) The proposed framework can automatically assess the bridge's health condition in real-time using only the vehicle's vibrations during its passage, even though minor erroneous determinations can be observed.

Even though some key findings can be observed, there are some influence factors that deserve further investigation, such as poor road roughness, temperature effects, and ongoing traffic. Our future work will initially explore the effects of these influence factors and test the effectiveness of the proposed method in field tests.

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