Automatic Drive-By Bridge Damage Detection via a Clustering Algorithm

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Abstract. Over the past two decades, the drive-by bridge inspection method as an active field of research has been proven to be effective by many studies. Meanwhile, with the recent growth and advancement in Machine Learning (ML) techniques, data-driven based Structural Health Monitoring (SHM) systems have piqued the interest of many scholars, as they have the potential to provide a fast and accurate solution to damage detection problems. Although some efforts have been made, the integration of ML techniques with drive-by methods still faces obstacles. For example, many data-driven drive-by approaches are based on supervised learning models requiring labels for different damage cases, while the damage labels are rarely available in practice. Additionally, their performance relies on a few extracted features from ML approaches, which are often not applicable to different bridges. Given this background, a novel automatic damage detection algorithm for the indirect SHM framework is proposed. It employs a cluster-based ML model and proposes a new damage index to indicate the damage and to update the database. The vehicle accelerations collected from a healthy bridge as labeled data are used to train the model. Using only raw vehicle accelerations as inputs, the proposed model can indicate the damage in real time and update the database automatically. Laboratory experiments are performed to validate the proposed methodology by employing a steel beam and a scale truck model. The results demonstrate the model's feasibility and robustness, and suggest the potential of achieving automatic, efficient, and practical SHM systems in the future.

Keywords: Automatic detection · Drive-by inspection · Vehicle-bridge interaction · Damage indication · Clustering

1 Introduction

In recent decades, bridge maintenance and monitoring have become widespread concerns around the world [1]. However, direct SHM methods have long been considered expensive due to the enormous costs associated with sensor installation and maintenance [2]. Moreover, because the instrumentation is permanently fixed on the bridge as a tailored SHM system, it can be challenging to transfer one monitoring system to other bridges [3]. These drawbacks restrain the broad application of direct SHM methods on bridges, and there is a need to develop an alternative strategy without instrumenting the bridge.

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Due to its advantages in mobility, economics, and efficiency, the drive-by bridge inspection method, an indirect SHM method, has attracted a lot of interest recently. Studies have verified the feasibility of the drive-by approach in extracting bridge modal parameters (e.g., fundamental frequencies and mode shapes) via numerical simulations, laboratory experiments, and field tests [4–7]. Changes in modal parameters could indicate bridge deterioration, which is referred to as the modal parameter-based approach.

Most modal parameter-based approaches, however, are not sensitive to small-scale damages and do not perform satisfactorily for a variety of reasons. First, modal parameters (e.g., frequencies) are usually affected by environmental factors (such as temperature), and they do not provide sufficient information to indicate damage [8]. Second, mode shapes or their derivations are prone to measurement errors, masking changes from minor damage [9]. Third, they heavily rely on the knowledge and experience of researchers for the damage determination, with the risk of human bias. Although there are some approaches based on indicators like displacement profile and moving force, similar issues have been observed as well [10–12].

ML methods can leverage the whole time-domain or frequency-domain responses rather than just peaks in the spectrum [13]. They have high accuracy in damage detection and are sensitive to small-scale damages [14]. So far, there have been some studies on the application of ML techniques to the drive-by method. For example, Cerda et al. [15] effectively identified bridge damage states using Support Vector Machines (SVM) and input from vehicle vibration data. In 2019, Artificial Neural Network (ANN) was first applied to indirect SHM problems by Malekjafarian et al. [16], acquiring outstanding results for bridge damage detection. Though encouraging results have been attained, these approaches necessitate numerous labelled samples in order to fit the model (i.e., supervised learning), which is difficult in practice. On the other hand, most current non-supervised learning models are based on features extracted from ML techniques (e.g., autoencoders) [13, 17]. One concern is that such features are usually not applicable to other bridges, and they often demand the evaluation of feature extraction methods over raw dynamic measurements [18]. Thus, it is important to propose a robust and universal feature for damage detection.

This paper proposes a new damage index and an automatic damage detection algorithm for the indirect SHM framework. A numerical investigation is first carried out to study the relationship between the vehicle time-domain response and the bridge damage, based on which a new damage index is proposed. A novel clustering ML model is then designed to indicate the damage and automate the detection process. The proposed methodology is validated by a database built from laboratory experiments using a steel beam and a scale truck model. The method only requires vehicle accelerations collected from a healthy bridge to train the model. It can give instant feedback on damage or update the database automatically after a vehicle passage, enabling real-time bridge damage detection.

2 Numerical Investigation

As mentioned above, numerical studies are herein conducted to investigate the relationship between the vehicle time-domain response and the bridge damage. The purpose of this section is to propose a physics-based damage index that can be widely used to indicate damage. To strike a balance between model complexity and computational efficiency, a 2-degree-of-freedom (DOF) vehicle model is used in this study, as illustrated in Fig. 1. The following equations provide the governing coupled equations for the vehicle-bridge interaction (VBI) system:

$$[M_v]\{\ddot{u}_v\} + [C_v]\{\dot{u}_v\} + [K_v]\{u_v\} = \{F_{cv}\} \tag{1}$$

$$[M_b]\{\ddot{u}_b\} + [C_b]\{\dot{u}_b\} + [K_b]\{u_b\} = \{F_{cb}\} \tag{2}$$

where $[M_v]$, $[C_v]$, and $[C_v]$ are the mass, damping, and stiffness matrices of the vehicle, respectively; $[M_b]$, $[C_b]$ and $[K_b]$ represent the mass, damping, and stiffness matrices of the bridge model, respectively. In the equations, $\{u_v\}$ is the displacement vector of the vehicle and $\{u_b\}$ is the nodal displacement of the bridge system. $\{F_{cv}\}$ and $\{F_{cb}\}$ stand for the time-varying interaction forces on the vehicle and the bridge, respectively.

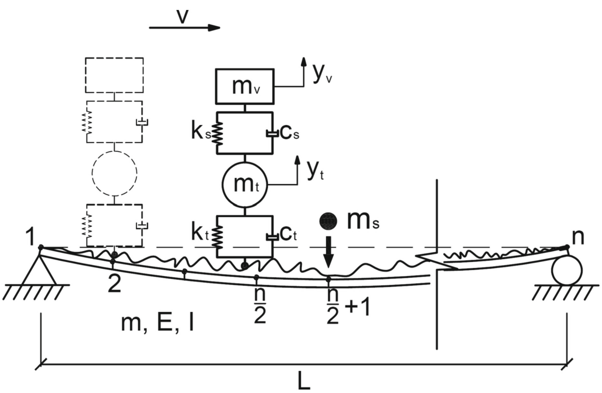


Fig. 1. VBI model.

The subsystem matrices and response vector for a 2-DOF vehicle model are as follows:

$$[M_v] = \begin{bmatrix} m_v & \\ & m_t \end{bmatrix} \tag{3}$$

$$[C_v] = \begin{bmatrix} c_s & -c_s \\ -c_s & c_s + c_t \end{bmatrix} \tag{4}$$

$$[K_v] = \begin{bmatrix} k_s & -k_s \\ -k_s & k_s + k_t \end{bmatrix} \tag{5}$$

$$\{u_v\} = \begin{bmatrix} y_v & y_t \end{bmatrix}^T \tag{6}$$

where m_v and m_t are the body and axle masses; c_s and c_t stand for the suspension and tire damping; k_s and k_t denote the suspension and tire stiffnesses; y_v and y_t are the vertical displacements of the vehicle body and the axle.

The road surface roughness can be simulated according to ISO 8608 [19]. There are eight classes, ranging from Class A (the best) to Class H (the worst), each corresponding to a different degree of road roughness; level A is selected to represent the road condition of the experiment in this paper.

The bridge is modelled as a simply supported Euler-Bernoulli beam, with two DOFs at each node (vertical translation and rotation). It has a length of L, a uniform flexural rigidity of EI, and a mass per unit length of m. Mass-stiffness proportional Rayleigh damping is used to simulate the bridge's damping. In laboratory experiments or field tests, real damage should be avoided if possible. Typically, the damage can be simulated by adding mass to the bridge [13–15]. Assuming that the beam has an even number of elements, the mass matrix of the bridge model after adding the mass to the mid-span can be expressed as follows:

$$[M_{b'}] = [M_b] + Diag(0 \ldots 0, m_s, 0 \ldots 0) \tag{7}$$

where $Diag(\bullet)$ denotes the diagonal operator; the additional mass, m_s, is the n-th value (n-th DOF) in the diagonal operator and the rest are zeros.

The VBI process can be solved by employing the Newmark-Beta method to acquire the vehicle's dynamic responses ($\beta = 0.25$, $\gamma = 0.5$). The bridge and vehicle parameters are chosen as $m = 1250$ kg/m, $EI = 2.6 \times 10^{12}$ N $\bullet$ m^2, $L = 45$ m, $m_v = 1.6 \times 10^4$ kg, $m_t = 7 \times 10^3$ kg, $c_s = 1.0 \times 10^4$ N $\bullet$ s/m, $c_t = 0$, $k_s = 4 \times 10^5$ N/m, $k_t = 1 \times 10^4$ N/m, and $v = 9$ m/s. These parameters can simulate the real-scale VBI models of the laboratory beam and car models used in the study.

Figure 2a shows the original acceleration responses from the healthy and damaged beams, in which they have similar curve shapes. Residual acceleration curves can be obtained by deducting the accelerations of the damaged case from the healthy case, as presented in Fig. 2b. It is found that the residual acceleration grows steadily as the damage increases from 1% to 3% (mass increases). A new damage index, DI, can be defined as Eq. (8), which is used for mass increase as artificial damage; it considers the contributions of all acceleration amplitudes. This index can be used to indicate structural damage, and it can be proven that such an index is not limited to a particular VBI system.

$$DI = \Delta A = \sum_{i=1}^{n} (|\ddot{y}_i^H - \ddot{y}_i^D|)\Delta t(8) \tag{8}$$

3 Diagnostic Algorithm

Although the above section theoretically proposes an index that can be used to indicate the occurrence of damage, it still needs to solve some issues in engineering applications. These include the measurement errors/noise, speed variance, and enormous data volumes. The designed algorithm (see Fig. 3) aims to apply the methodology proposed in the numerical study to practical engineering and achieve automatic bridge damage detection. It consists of three stages, which are data processing, model training, and damage detection.

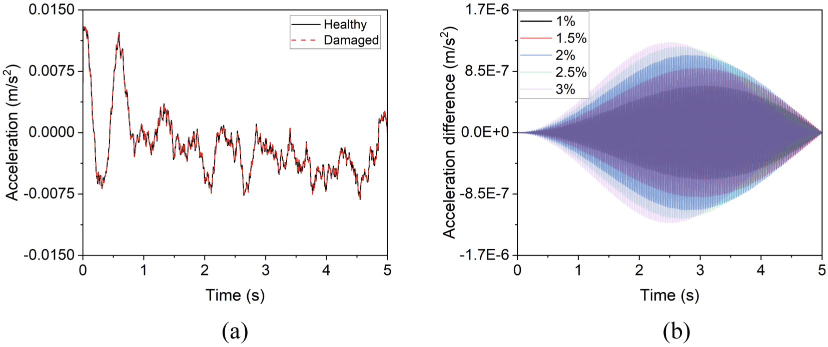


Fig. 2. Comparison of vehicle responses: (a) original accelerations, (b) residual accelerations.

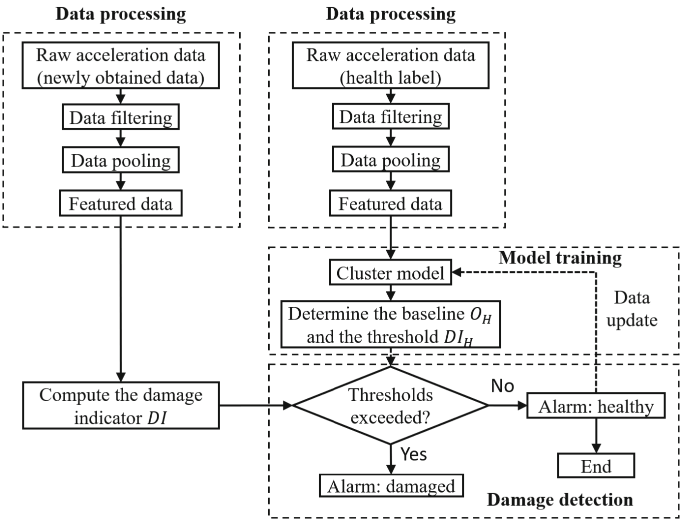


Fig. 3. Algorithm framework.

As shown in Fig. 4, the data processing stage includes data filtering and pooling. They are sliding window-based methods, where the processed time-domain signals are utilized as inputs for the next stage. In the study, the experiments were conducted in a normal laboratory environment, where white noise was the main source of noise. Thus, the Gaussian function is chosen as the window function for the filtering process, where the expected value and deviation are set to be 0 and 20, respectively. For the pooling process, the max operator is used since it has been demonstrated to be more informative in practice [20]. Data pooling can be regarded as a sliding window process with a stride equal to the window length; the window length is automatically modified with each run, and the data size in this study is set to be 450. Zeroes will be automatically added to the end of any data that cannot be split by 450, which have been shown to have little effect on the results based on the numerical investigation. The purpose of the data processing is to denoise raw data, equalize data size, and reduce computational costs.

Following processing, the featured data are used as inputs in the cluster model (KNN) to determine the coordinates of the cluster center, O_H, which is regarded as a representation of the health data (baseline). When there is only one cluster center, KNN can be simplified as follows:

$$O_H = (1/|H|) \sum_{x^{(i)} \in H} x^{(i)} \tag{9}$$

where $|H|$ denotes the number of samples in the cluster H (health set); $x^{(i)}$ is a labelled sample in the health set.

Using Eq. (8), the DI value for each sample in the health set can be computed, and it is empirically shown that the samples are normally distributed; the 95th percentile of the distribution is defined as the threshold, DI_H. In the damage detection stage, newly obtained data are compared to the baseline, and if their DI values are higher than the threshold, an alert will be triggered to warn of a potential damage occurrence. Data below the threshold, meanwhile, will be labeled as healthy and utilized to update the dataset, in addition to being notified as healthy.

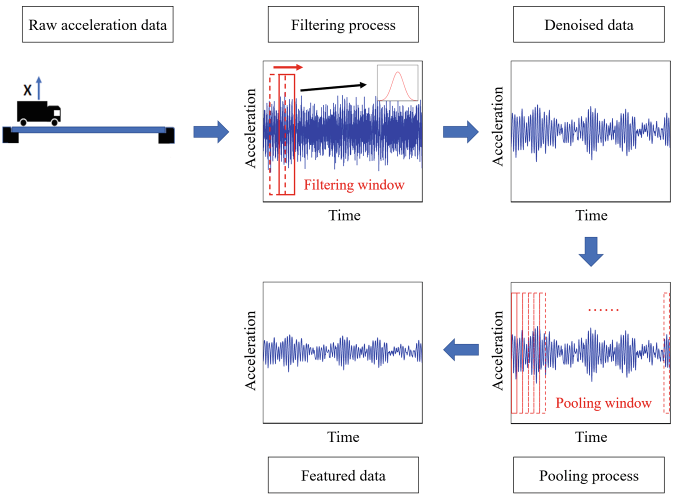


Fig. 4. Data processing.

4 Experimental Study

4.1 Experimental Setup

Bridge model: The physical properties of the beam model (HEA400) are listed as follows: elastic modulus $E = 199$ GPa; density $\rho = 7.85 \times 103$ kg/m^3; length $L = 4.4$ m; section area $A = 15898$ mm^2, and moment of inertia $I = 8.564 \times 10^7$ mm^4. The details of the bridge model, including the sectional dimensions, are shown in Fig. 5. The setup includes an acceleration ramp, a deceleration ramp, and a wire system that is used to guide the vehicle to travel through the beam in a straight line and along the same path. The layout of the beam model is shown in Fig. 6a. Mass is added to the mid-span bridge as artificial damage (see Fig. 6b).

Vehicle model: Tamiya's Mercedes-Benz 1850L is employed as the vehicle model (see Fig. 7a). Except for the weight, this engine-driven 1/14 scale model (568 mm × 202 mm) realistically captures the configuration of a full-sized truck. The self-weight of the vehicle model is 4.05 kg, and a 5-kg mass is added inside the vehicle body; thus, the overall vehicle weight is 9.05 kg. An accelerometer is mounted on the rear axle of the vehicle model as shown in Fig. 7b. The data acquisition system, which is PC-driven and has a sampling rate of 2 kHz, is used in the experimental tests; it is connected with sensors via wires. The velocities maintain similar in each run. In this study, the velocity distribution is between 0.78 m/s and 1.02 m/s, and the mean speed is 0.87 m/s.

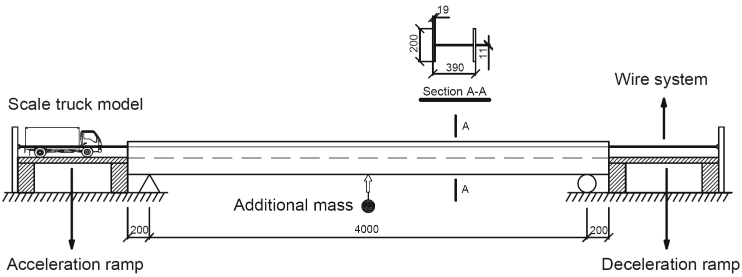


Fig. 5. Details of the bridge model (unit: mm).

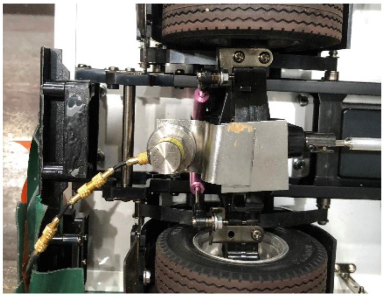
(a) Beam model layout

(b) Additional mass

Fig. 6. Beam model layout and additional mass on the beam.

Experimental dataset: For the proposed algorithm, only data from the intact state of the bridge are required to train the model. The vehicle is driven across the bridge repeatedly to acquire the experimental dataset. There are totally one healthy case and four damaged cases in the study, where the damaged cases are used as unknown inputs (or newly obtained data) to validate the algorithm. The healthy state has 200 vehicle

(a) Scale vehicle model



(b) Vehicle sensor installation

Fig. 7. Scale vehicle model and vehicle sensor installation.

runs, whereas the other states have 50 runs each, which may correspond to fewer and unbalanced damage samples in practice. The description of the damaged cases can be seen in Table 1. Only the rear axle sensor data are used in this study, but in fact the results of the front and rear axle data are similar, which has been confirmed by many studies [13–15]. Thus, the experimental dataset has 200 (runs) × 1 (healthy case) × 1 (sensor) + 50 (runs) × 4 (damaged cases) × 1 (sensor) = 400 (signals).

Table 1. Damaged case description.

Case No	Location	Weight	Runs	Case No	Location	Weight	Runs
1	Mid-span	2 kg (0.4%)	50	2	Mid-span	4 kg (0.8%)	50
3	Mid-span	6 kg (1.2%)	50	4	Mid-span	10 kg (2%)	50

4.2 Results and Analysis

Through the training process, the threshold of the healthy state, DI_H, can be calculated as 1.75×10^{-2} (95% confidence). The baseline is the coordinate origin. As presented in Fig. 8a, the statistical distributions of DI values for the healthy case and case 1 are close, and they roughly follow the normal distribution. In this situation, only about 68% of the damaged samples can be correctly identified, or the accuracy rate is 68%. When the damage (structural change) increases to 0.8%, the accuracy rate rises sharply to 100% (see Fig. 8b), which means that the method is sensitive to structural change that is greater than 0.8%. For all cases, their distribution of DI values can be referred to Fig. 9. Except for case 1, samples in other damaged cases can be effectively identified by the present algorithm. Additionally, the convergence of DI will be an interesting issue to be investigated, which will be explored in future studies.

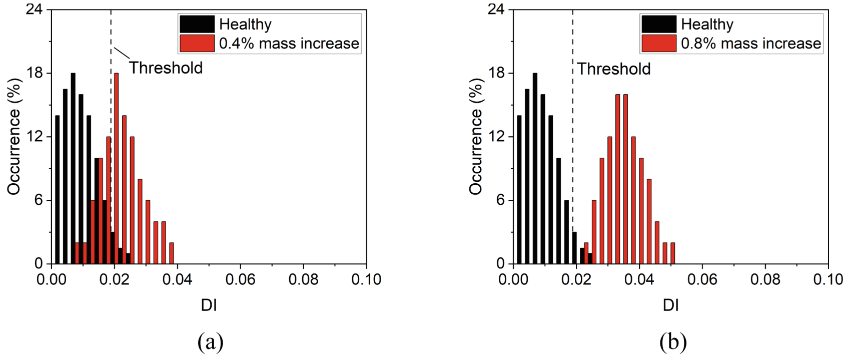


Fig. 8. Damage indication performance: (a) 0.4% mass increase, (b) 0.8% mass increase.

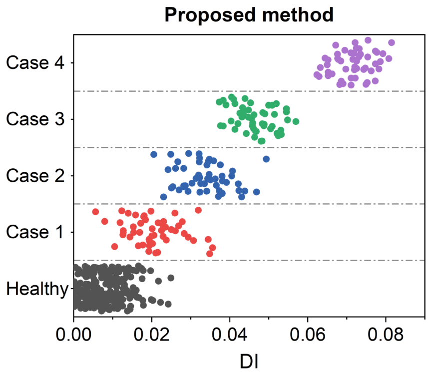


Fig. 9. *DI* distribution for all cases.

5 Conclusion

In this paper, a novel automatic damage detection algorithm for the indirect SHM framework is proposed. It presents a new damage index and a cluster-based ML model to indicate the damage in real-time and update the database automatically. Experiments are conducted to validate the proposed algorithm by employing a steel beam and a scale truck model. Based on the results, the following conclusions can be drawn:

(1) The proposed damage index can effectively indicate damage, which in this study is the mass increase.
(2) The proposed diagnostic algorithm is sensitive to damage. The damage (structural change) to a degree of 0.8% may be effectively detected in the lab tests in this study.
(3) The validity of real-time bridge damage detection utilizing only raw vehicle acceleration data is demonstrated in this study.

Future work needs to verify the robustness of the algorithm under more realistic and complex conditions, like a full-scale test in practice.

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