Lan, Yifu; Zhang, Youqi; Lin, Weiwei

Diagnosis algorithms for indirect bridge health monitoring via an optimized AdaBoost-linear SVM

Published in:
Engineering Structures

DOI:
10.1016/j.engstruct.2022.115239

Published: 15/01/2023

Document Version
Publisher's PDF, also known as Version of record

Please cite the original version:
Lan, Y., Zhang, Y., & Lin, W. (2023). Diagnosis algorithms for indirect bridge health monitoring via an optimized AdaBoost-linear SVM. *Engineering Structures*, *275*, Article 115239.
https://doi.org/10.1016/j.engstruct.2022.115239

Engineering Structures 275 (2023) 115239

Contents lists available at ScienceDirect

Engineering Structures

journal homepage: www.elsevier.com/locate/engstruct

Diagnosis algorithms for indirect bridge health monitoring via an optimized AdaBoost-linear SVM

Yifu Lan, Youqi Zhang, Weiwei Lin *

Department of Civil Engineering, Aalto University, 02150 Espoo, Finland

ARTICLE INFO

Keywords:
Drive-by bridge inspection
Vehicle-bridge interaction
AdaBoost SVMs
Health state identification
Data-driven SHM

ABSTRACT

A data-driven approach based on Optimized AdaBoost-Linear SVM is proposed to indicate the bridge damage using only raw vibration signals received from a vehicle passing over the bridge. To enable Linear SVM as an effective component learner in AdaBoost and to achieve its best generalization performance, an optimizing strategy is designed to modify its configuration. Laboratory experiments are conducted to establish the dataset employing a steel beam and a scale truck model with an engine. The present algorithm learns to identify bridge health states by feeding training data, and its performance is assessed using the testing dataset. Principal Component Analysis (PCA) as a dimension reduction technique is utilized to visualize the identification results. From the dataset on diverse health states, the proposed strategy can identify the bridge damages effectively and provide better generalization performance than other commonly used algorithms. When compared to other algorithms such as SVM and Random Forest, it improves result accuracy by 5% to 16.7%. The experimental results also indicate that the vehicle-based indirect Structural Health Monitoring (SHM) framework can be equally effective as the direct SHM systems, and suggest the potentials of achieving automatic, robust and practical SHM models in the future.

1. Introduction

Bridge structural deficiencies have become a widespread concern throughout the world due to increasing traffic loads and the progressive degradation of bridges over time etc. [1]. It is reported that more than 11 % of bridges in the United States are structurally deficient [2]; in Europe, most bridges were constructed from 1945 to 1965 [3]; in Australia, 72 % of the bridge transportation network was built before 1976 [4]; in Japan, the boom of bridge infrastructure development occurred between 1955 and 1975, and many of these bridges are predicted to have structural flaws within the next decade [5]. As a traumatic example, the Genoa bridge collapse in Italy claimed the lives of forty-three people in 2018, primarily due to poor maintenances with difficulties in inspection [6]. In light of this, it is critically important to develop low-cost but effective Structural Health Monitoring (SHM) systems capable of detecting potential damages in the early stage.

The current bridge monitoring framework is known as the "sensor-based monitoring" system, in which numerous sensors directly attached to the structure are required, and their performances highly depend on the sensors' location and sensitivity etc. [7]. Because of the tremendous costs in sensor installation and maintenance, conventional direct SHM techniques have been considered as expensive approaches for many years. On-site instrumentation on bridges is usually costly, risky, and laborious, especially for a bridge under ongoing traffic or in a hazardous location [8]. Additionally, sensors on the bridge are highly susceptible to be broken due to environmental impacts like weather, resulting in high maintenance and repair expenses [9]. Furthermore, one monitoring framework can be difficult to transfer to other bridges, as the instrumentation is fixed permanently on the bridge as a tailored SHM system [10]. These disadvantages limit the widespread application of direct SHM technologies on bridges in general, and there is a need to develop an alternative strategy without instrumenting the bridge.

Giving the merits in mobility, economy and efficiency, an indirect SHM method, known as the drive-by bridge inspection method, has become increasingly popular as an active field of research in recent years [11]. The bridge vibrates as the vehicle passing over it and the dynamic properties of bridges will be reflected in vehicle response through the coupling effects between them, referred to as Vehicle-Bridge Interaction (VBI) [12]. As a result, this method does not require vibration sensors to be placed on the bridge, but only a few sensors mounted on the vehicle

* Corresponding author.
E-mail address: weiwei.lin@aalto.fi (W. Lin).

https://doi.org/10.1016/j.engstruct.2022.115239

Available online 14 November 2022

passing through it, where the vehicle is served as both exciter and receiver [13]. Studies have investigated the potentials of the drive-by bridge inspection approach in obtaining bridge modal parameters, such as fundamental frequencies and mode shapes [14–17]. Changes in modal parameters could indicate bridge deterioration as shown in many research works, which is referred to as the modal parameter-based monitoring approach [18–21].

However, most modal parameter-based methods fail to achieve satisfactory performance and are not sensitive to small-scale damages due to several reasons. Firstly, natural frequencies as the damage indicator employed by many studies did not have sufficient information for damage indication. They are easily influenced by environmental factors (e.g., temperatures), which will mask the subtle change induced by damages [22,23]. Secondly, mode shapes or their derivations, as the other commonly used indicator, are usually subject to measurement errors, disguising changes from small-scale damage [24]. Thirdly, most modal parameter-based approaches highly rely on the knowledge and experience of researchers for the damage determination with risks in human bias. Although there are some methods based on indicators like damping, displacement profile and moving force, similar problems have been discovered as well [25–28]. Machine Learning methods can exploit the complete time-domain and frequency-domain responses rather than just peaks in the spectrum and are sensitive to tiny changes in the signal [24,29,30]. They have the potential to resolve these issues by providing higher accuracy in detection results and the possibility of identifying small damages, which is the motivation for this work.

ML methods have been widely used in direct SHM frameworks and have demonstrated excellent performance. For example, Alamdari et al. [31] employed K-Nearest Neighbors algorithms (KNN) to successfully identify the health state of Sydney Harbor Bridge in Australia under ongoing traffic. A multi-level assessment strategy and a decision support framework were used by Shu et al. [32,33] to assess the load-carrying capacity and structural behavior of bridges. Zhang et al. [24] achieved accurate classification of 0.0015 % structural mass increase of steel girder bridges via Convolutional Neural Networks (CNNs). It is worth noting that, despite the widespread success of ML applications in SHM problems, as a data-driven method, there are still some drawbacks: 1. ML methods usually do not have a clear physical explanation [34,35]; 2. ML methods often require pre-knowledge of the health status as "baseline", which means they are unable to identify pre-existing damages [24,36]. While there have been few studies and implementations of ML techniques on the indirect SHM method using passing vehicles. Based on Support Vector Machines (SVMs), Cerda et al. [36] and Lederman et al. [37] successfully detected and classified different bridge damage types with acceleration data from a passing vehicle. In 2019, Artificial Neural Network (ANN) was firstly applied to the vehicle-based bridge health monitoring system by Malekjafarian et al. [38], obtaining promising results. These studies verified the "potential" of ML techniques in indirect SHM frameworks, but there is still much space for development in comparison to their deployment in direct SHM systems.

As prevalent methodologies, artificial neural networks and similar methods often have complicated architectures and hyperparameters, require huge computing resources, and are difficult to tune due to issues like local minima [39]. An important concern is that too many hyperparameters and overly complex algorithm structures might bind the algorithm to a particular system or framework, which is hard to transfer to others. The initial intention of this paper is to design a simple and computationally efficient approach framework that has superior performance in damage identification. SVMs, developed from the theory of Structural Risk Minimization, are one of the most robust ML strategies, which find an optimal separating hyperplane in the feature space to maximize the width of the gap between the two categories [40]. Several studies show that SVMs perform well on health state classification problems with the presence of noticeable structural damages [41–42]. In terms of small-scale damages, however, their dynamic responses are highly similar to those of health, for which SVMs and other general classifiers are likely to perform poorly. AdaBoost, which enhances the classifier's performance by learning from misclassified samples, can be used as a boosting strategy in this case. It builds a collection of component classifiers by keeping a set of weights over training samples and adaptively adjusting these weights after each boosting iteration: the weights of training samples that are misclassified by the current component classifier will be increased, while the weights of training samples that are correctly classified will be decreased [43]. The boosting mechanism forces SVM component classifiers to focus on misclassified samples from the minority class, preventing the minor damage characteristics from being considered as noises. This could justify the exploration of AdaBoost with SVM component classifiers in the indirect SHM framework.

The integration of SVMs with AdaBoost, however, still remains challenging. This is because SVMs, as conventional strong classifiers, seem to go against the "moderate classifier" principle in boosting strategies, and AdaBoost cannot train a strong classifier easily. To benefit from AdaBoost methods, previous studies adjust the kernel coefficient, *gamma,* for 'RBF', 'poly' and 'sigmoid' SVMs, defining how far the influence of a single training example can reach, to weaken their learning abilities as component classifiers [44–45]. While the regularization parameter, *C*, which governs the model complexity and training errors, can also affect the SVMs' performance. According to Li et al. [46], seeking the best *C* and *gamma* values at the same time to achieve the greatest generalization performance of AdaBoost-SVMs is not feasible, which is also accompanied by a large computational cost. On the other hand, the existing algorithms do not explicitly take significant measures to address this issue. In this paper, the authors use a linear SVM as the base classifier in AdaBoost because linear and simple classifiers could better separate the high-dimensional spaces composed of vibration data in general. Linear SVM lacks *gamma*; instead, its performance is controlled by merely-one parameter, *C*, whose effects are herein crucial. While the influence of *C* value on AdaBoost-SVMs has not received sufficient attention in prior studies, and it will be investigated in this paper. Meanwhile, it provides a "convenient" way to tune by adjusting the *C* value only in order to find a proper SVM classifier. Based on this, an optimization strategy can be designed to achieve the improved generalization performance of AdaBoost-Linear SVM by globally seeking the *C* value.

This paper adopts a novel approach for damage indication on the indirect SHM framework, based on a combination of AdaBoost, Linear-SVM and an efficient optimization method for *C* value to improve the result accuracy. Using raw vehicle acceleration signals as inputs, the present algorithm, which combines the advantages of linear SVM and AdaBoost, is designed to adaptively update its configuration by the proposed optimization strategy to acquire the optimum generalization performance. This paper aims to address the following concerns of interest: (1) whether the proposed strategy can be employed as an effective classifier in health state identification problems with raw vehicle acceleration signals as direct inputs; (2) will this algorithm provide improvements or benefits over the existing ML methods; (3) how does the algorithm boost the performance in damage indication. Experiments are conducted to obtain the dataset for training and testing by employing a truck model and a steel beam. The effectiveness of the strategy is evaluated by its accuracy on classifying the testing sets of various health statuses. Meanwhile, algorithms such as SVMs are used to compare the results. Principal Component Analysis (PCA) techniques are used to visualize the classification results. The experimental results from the vehicle are also compared with those obtained directly from the bridge model to demonstrate the feasibility of the indirect SHM framework.

The contributions of the work are summarized as follows: Firstly, the influence of C value on AdaBoost-SVMs is investigated and an optimization method is designed to achieve the improved generalization performance. Secondly, this paper presents an early attempt of experimentally validating the feasibility of drive-by bridge inspection to identify small-scale structural changes in the bridge using data-driven frameworks. Thirdly, experiments are performed, and the results are used to validate the high efficiency of the proposed method. Lastly, by comparing the performance of different machine learning methods on the indirect SHM system, this paper provides a useful reference for future exploration of the drive-by method based on data-driven frameworks.

2. Methodology

2.1. Overview of the SHM framework

The indirect SHM model is designed as a four-step process as shown in Fig. 1. In step 1, vehicle acceleration records from both healthy and damaged states with the sampling frequency of F_H Hz are divided into NH and ND numbers of vectors, in which NH and ND are the total vehicle runs for each health state. In step 2, effective acceleration signals of T_H^i seconds in healthy condition for the *i-th* run ($i = 1,2,3, \ldots, NH$) and signals of T_D^j seconds in damaged condition for the *j-th* run ($j = 1,2,3, \ldots, ND$) are selected, during which the whole vehicle is on the beam, referred to as the valid acceleration segments. The time segments would be identical in this study ($T_H^i = T_D^j = T$), as the vehicle speed is controlled to be approximately constant. Thus, both vectors H_i and D_j contain $T \times F_H$ discrete points, respectively, which refer to the information about the bridge in intact and damaged situations obtained by the *i-th* and *j-th* runs. In step 3, the designed model is trained by feeding the training data, evaluating the losses, iteratively updating the weights from misclassified samples and adaptively modifying the configuration. In step 4, the validation procedure examines the model's performance in damage indication based on testing sets. Steps 1 and 2 are known as the signal pre-processing stage, while steps 3 and 4 represent the damage diagnosis stage.

2.2. Signal preprocessing

Raw acceleration signals received from the passing vehicle should be processed to establish the dataset for the Optimized AB-Linear SVM model. Fig. 2 illustrates the preprocessing procedure for vehicle acceleration records. For the *i-th* and *j-th* runs in healthy and damaged bridge states, valid acceleration segments should be cut off after the acquisition of vehicle acceleration signals, which contain required information about the bridge. Generally, peaks can be found in the acceleration records of the front axle when the vehicle enters and exits the bridge due to expansion joints at both ends, which are regarded as an indicator for selecting effective signal segments. Valid acceleration segments are selected as the signal records, during which the entire vehicle is on the bridge, with the time periods of T. Given a sampling frequency of F_H, there are totally $T \times F_H$ discrete points in the valid segments of healthy and damaged bridges. The valid acceleration segments in time domain, which could preserve the health state information to the largest extent, are used as direct inputs for Optimized AB-Linear SVM. The acceleration amplitudes are utilized as features, and AdaBoost-SVM as the machine learning model aims to categorize data points constituted of acceleration amplitudes in a high-dimensional space. If all vectors have been processed, matrices M_H, M_D with shapes of $N_H \times (T \times F_H)$ and $N_D \times (T \times F_H)$ corresponding to healthy and damaged states, respectively, can be built as the dataset for the designed model.

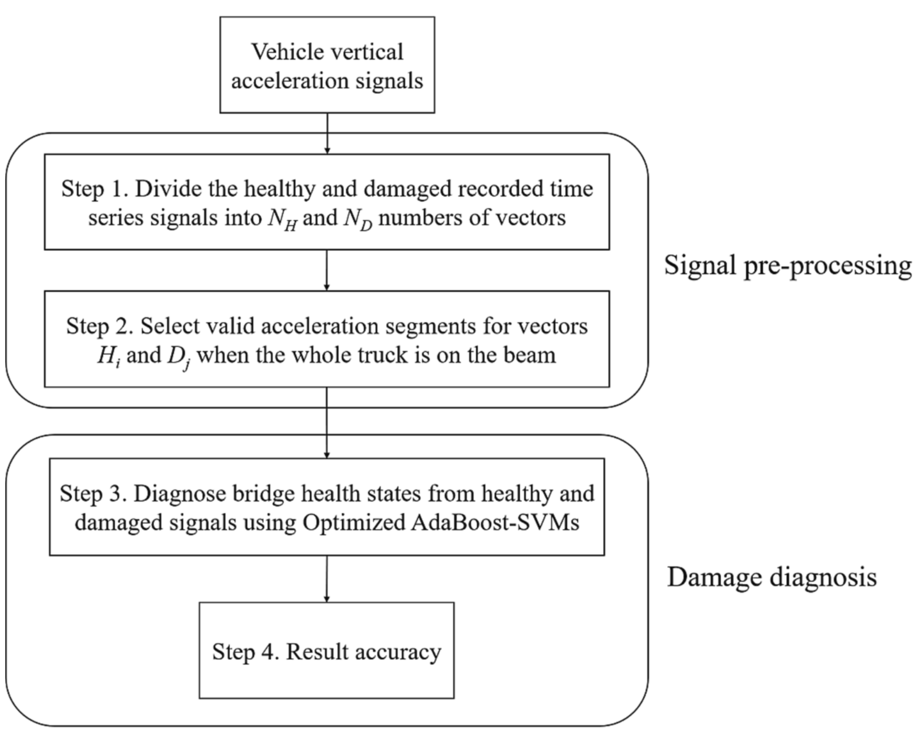


Fig. 1. Architecture of the designed SHM model.

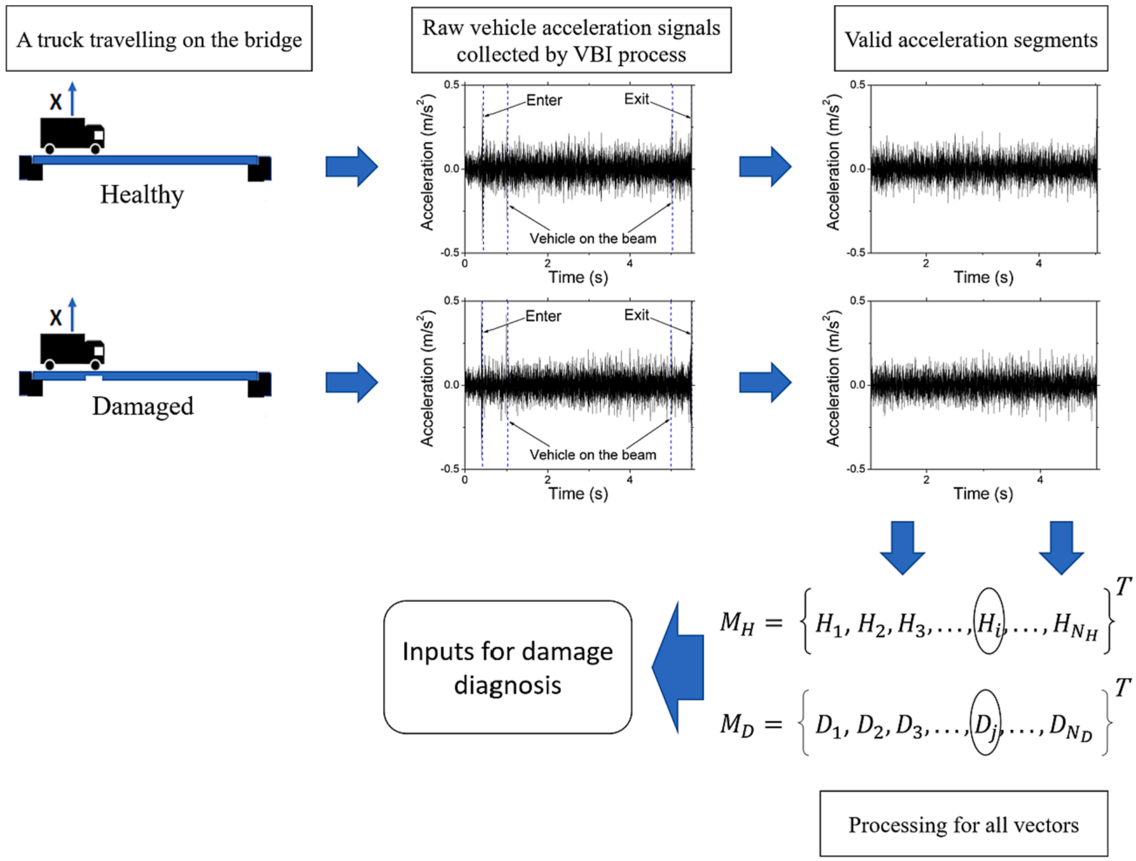


Fig. 2. Signal preprocessing procedure.

2.3. Proposed algorithms

This section aims at employing SVMs with Linear kernel as component classifiers in AdaBoost and seeking its best generalization performance in damage identification. SVMs are strong classifiers and there is a need to weaken their learning abilities to enable them to be effective component learners for AdaBoost. Unlike other SVM algorithms with multiple parameters, Linear SVM's performance merely depends on the regularization parameter, C, and its learning capacity can be changed by simply adjusting the C value. It could not benefit from a C value that is too large or too small, and a proper C value should balance the "complexity" and "diversity" of the classifier. There may also be the optimum C values that can lead to the greatest generalization performance when utilizing Linear-SVMs as component learners in the AdaBoost approach. The proposed optimization strategy searches for the optimum C values that can maximize the generalization performance.

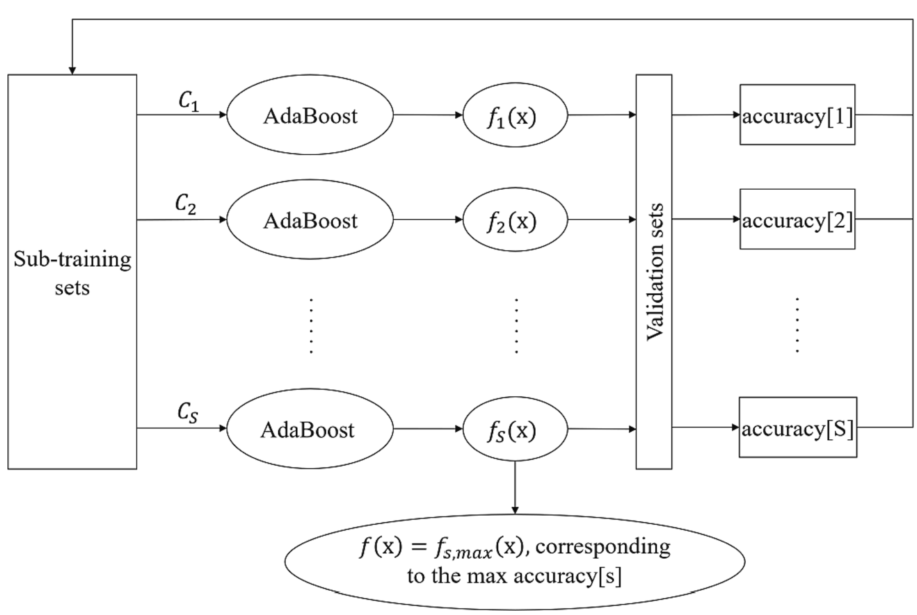


Fig. 3. Optimizing procedure.

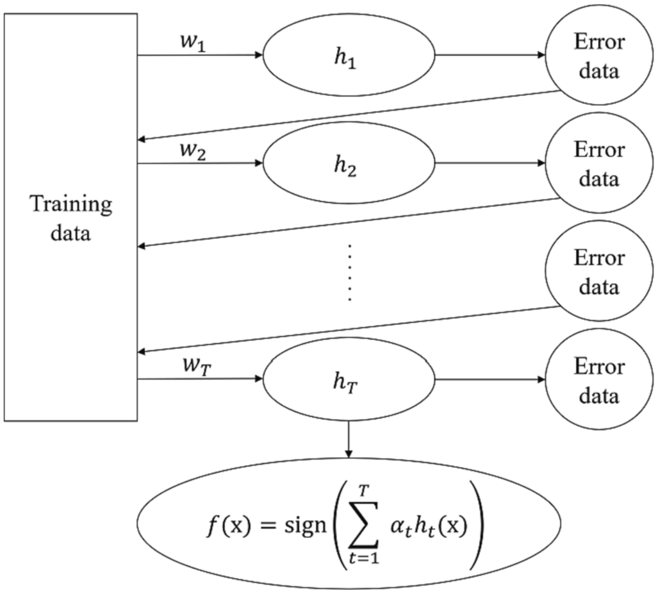


Fig. 4. AdaBoost training procedure.

Optimized AdaBoost-Linear SVM consists of two processes of optimization and training, as depicted in Fig. 3 and Fig. 4, respectively. The procedure of the complete algorithm is referred to as Algorithm 1. The training samples are divided into sub-training sets and validation sets with a ratio of 90 %: 10 %. In the optimizing process, a very small C value, C_{ini}, is initially set corresponding to a linear SVM classifier with the weak learning ability. Using sub-training sets as inputs, Linear-SVM with this C value is then trained by AdaBoost to return an accuracy on validation sets. After that, the C value is increased slightly by C_{step}, to enhance the learning ability of Linear-SVM. This procedure is repeated until the final cycle, S, is completed, from which the optimal classifier with the greatest result accuracy is chosen as the optimum classifier for the given dataset. In the training process, with the input of C value at the *s-th* cycle, AdaBoost maintains a weight distribution over sub-training samples with labels, which is initially configured to be uniform. Linear SVM as the component learner is called repeatedly in a series of cycles, T. At iteration t, Linear SVM trains a classifier, h_t, and the distribution, w^t, is updated in each iteration based on the prediction results on sub-training samples. Generally, correctly classified samples are given smaller weights, while misclassified samples are assigned larger weights. The values of C_{ini}, C_{step}, S and T required for the algorithm are set as 0.01, 0.1, 1000 and 50, respectively, in this study. Since the influence of the C value in AdaBoost SVMs has not been explicitly or thoroughly investigated in previous studies, their working mechanisms will be discussed in later sections with the acceleration data as inputs.

Algorithm 1. *Optimized AdaBoost-Linear SVM algorithm.*

Require: training samples with labels, $\{(\mathrm{x}_1, y_1),\ldots,(\mathrm{x}_i, y_i),\ldots,(\mathrm{x}_{N+M}, y_{N+M})\}$, where x_i represents the *i-th* vector in matrix $\{M_H, M_D\}^{\mathrm{T}}$; $y_i = \{-1,1\}$ for damaged and healthy labels; $N + M = N_H + N_D$ and $i = 1,2,3,\ldots, N + M$.

Require: component learner, Linear SVM.

Require: the number of cycles in updating the regularization parameter, *S*.

Require: the number of iterations at which boosting is terminated, *T*.

Require: the initial regularization parameter, C_{ini}; the step of regularization parameter, C_{step}.

1. Divide the training samples into sub-training sets and validation sets:

$M_{sub-train} = \{(\mathrm{x}_1, y_1),\ldots,(\mathrm{x}_i, y_i),\ldots,(\mathrm{x}_N, y_N)\}$; $M_{sub-validation} = \{(\mathrm{x}_{N+1}, y_{N+1}),\ldots,(\mathrm{x}_{N+j}, y_{N+j}),\ldots,(\mathrm{x}_{N+M}, y_{N+M})\}$,

where $\frac{N}{M} = 9{:}1$; $i = 1,2,3,\ldots, N$ and $j = 1,2,3,\ldots, M$.

2. Initialize the weights of sub-training samples, $w_i^1 = 1/N$ $(i = 1,2,3,\ldots, N)$.

3. for iteration s in S:

for iteration t in T:

(1) Train a Linear SVM component classifier, h_t, on the weighted sub-training set.

(2) Compute the training error of h_t: $\varepsilon_t = \sum_{i=1}^{N} w_i^t, y_i \neq h_t(\mathrm{x}_i)$.

(3) Set the weight of the component classifier h_t: $\alpha_t = \frac{1}{2}\ln\left(\frac{1-\varepsilon_t}{\varepsilon_t}\right)$.

(4) Update the weights of sub - training samples: $w_i^{t+1} = \frac{w_i^t \exp[-\alpha_t y_i h_t(\mathrm{x}_i)]}{C}$, where $\sum_{i=1}^{N} w_i^{t+1} = 1$.

Output: $f_s(\mathrm{x}) = \mathrm{sign}\left(\sum_{t=1}^{T} \alpha_t h_t(\mathrm{x})\right)$.

(1) Calculate the accuracy on validation sets: accuracy[s] $= \frac{TP+TN}{TP+TN+FP+FN}$, where TP, TN, FP, FN represent true positive, true negative, false positive and false negative predictions in samples.

(2) Increase C value by C_{step}: $C = C_{step} \times s + C_{ini}$

4. Output: $f(\mathrm{x}) = f_{s,max}(\mathrm{x})$ corresponding to the max accuracy[s].

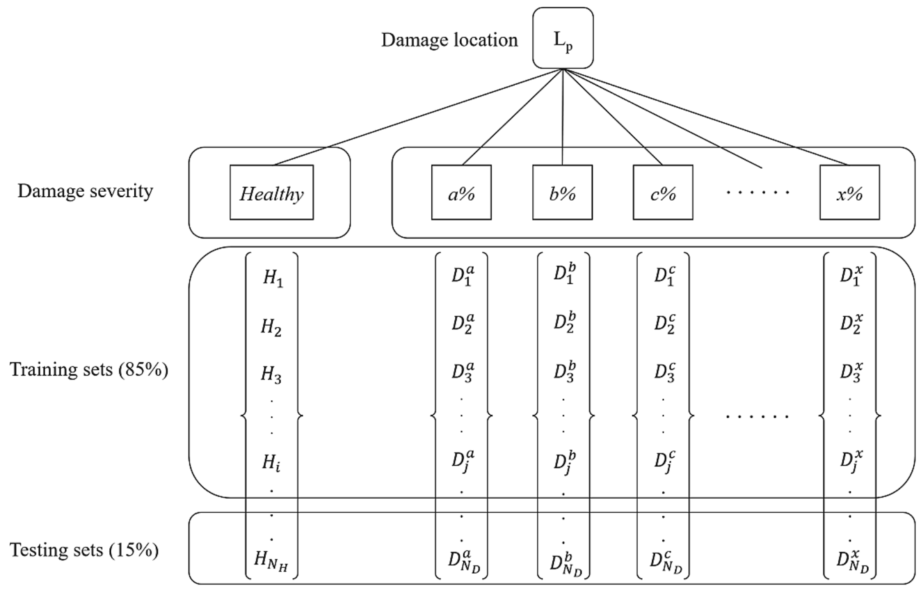


Fig. 5. Format of the dataset.

2.4. *Damage diagnosis*

Optimized AdaBoost-Linear SVM learns to identify bridge health states via training and validation processes. The whole database obtained from vehicle responses under diverse health statuses is split into training sets and testing sets as shown in Fig. 5. For a given location of damage, the strategy is trained by feeding the training data from different damage intensities (*a%, b%, …,x%*), modifying the parameters, computing the errors and iteratively updating the weights as indicated in Algorithm 1, which is the training step. In the validation step, the proposed algorithm's performance in damage indication is evaluated by the result accuracy in testing sets, which are set as 15 % of the whole dataset (85 % data are training sets) in the study.

3. Experimental program

Laboratory experiments are conducted by employing a steel beam and a scale truck model with an engine. Acceleration records collected from the vehicle sensors are used to establish the dataset for training and validating the proposed model. For the damage diagnosis model, data from both intact and damaged states are required. Instead of inducing actual damages to the structure, the damaged states are simulated by attaching masses to the beam in order to avoid permanent or irreversible destruction. This has been adopted by many studies to generate damage, which proves its feasibility, such as those conducted by Cerda et al. [37], Kim et al. [21], Zhang et al. [29] and Liu et al. [30]. The data acquisition system is the same for both the beam and the vehicle, which is PC-driven and connected with sensors via wires, with a sampling rate of 2000 Hz. The sensors used in the study are made by Bruel & Kjær (TYPE 4371), and relevant specifications are provided as follows: frequency range (0.1 – 12600 Hz), weight (11 g), and sensitivity (1.0 pC/ms^{-2}). Other parameters of the sensor can be referred to in its product data [47]. It is worth mentioning that, since the sensors are placed on the bridge model throughout the experiment, which can be regarded as a part of the weight of the bridge, their weights would not affect the results.

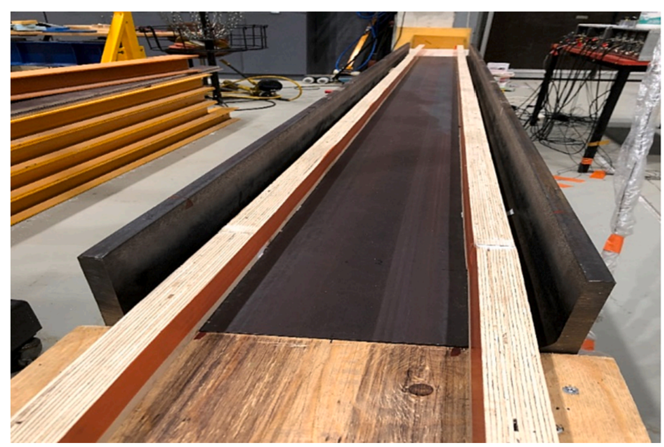


Fig. 6. Steel beam used as a bridge model.

3.1. *Bridge model setup*

A HEA400 simply supported steel beam was used to represent a bridge model in the experiment, as shown in Fig. 6. Physical properties of the steel beam are listed as follows: elastic modulus $E =$ GPa; density $\rho = 7.85 \times 10^3$ kg/m^3; length $L = 4.4$ m; section area $A = 15898$ mm^2 and moment of inertia $I = 85.64 \times 10^6$ mm^4. The dimension details of the cross-section are shown in Fig. 7. The fundamental natural frequency of the simply supported beam is measured as 35.4 Hz from the bridge spectrogram. The experiment contains an acceleration ramp and a deceleration ramp, as well as a guide rail that is used to adjust the vehicle's direction so that it can travel through the beam straightly. Masses are added to three different locations as artificial damages, and the details will be discussed later. As shown in Fig. 7, three accelerometers are instrumented at 0.1L, 0.5L and 0.9L of the steel beam, respectively, to record the bridge vibrations at different sections during the vehicle's passage. Fig. 8 indicates how the mass and the sensor are installed on the beam.

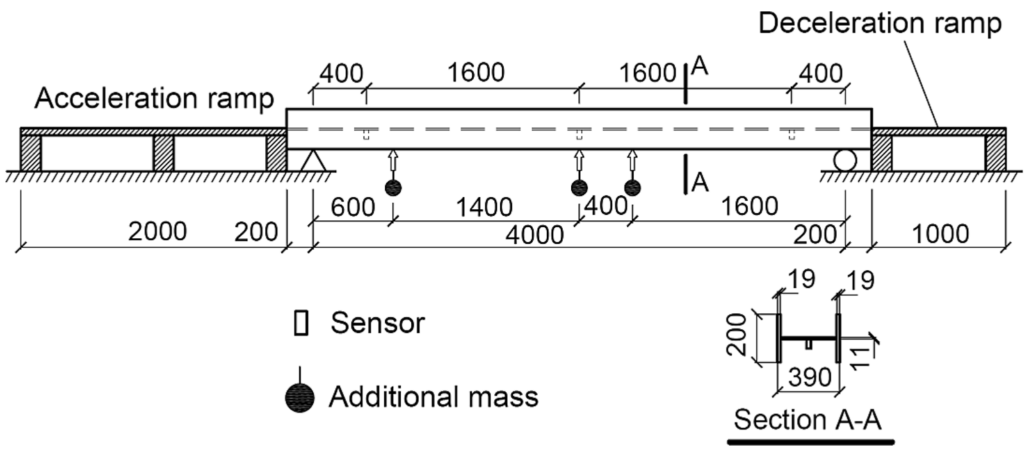


Fig. 7. Details of the experimental beam model setup.

(a) (b)

Fig. 8. Attachments on the beam: (a) Additional mass, (b) Accelerometer.

3.2. Vehicle model setup

Tamiya's Mercedes-Benz 1850L is used as the vehicle model as presented in Fig. 9. Tamiya is a Japanese manufacturer of various car models, known for its accurate scale details and outstanding quality. Except for the weight, this 1/14 scale model (568 mm × 202 mm) realistically captures the configuration of a full-sized truck. The weight of the vehicle itself is 4.05 kg according to the laboratory measurement (0.8 % of the bridge mass). Four accelerometers are mounted on the front of the car, front axle, rear axle and vehicle body, respectively, as described in Fig. 10. The loading weights are placed inside the vehicle body as shown in Fig. 11(a), and a 540-brushed type motor is used to drive the vehicle operated by an electric controller as presented in Fig. 11(b), (c). In such damage detection approach, the vehicle speed should be maintained the same or similar for different tests so that the variation of speed would not mask the true damage on the bridge [48]. A speed difference of around 40 % is empirically acceptable according to some previous studies [37,38,49]. An appropriate and relatively low speed is generally recommended for the drive-by inspection method [50], as it provides high-resolution information for damage detection. If the speed is too low, the excitation of the car may be insufficient to cause a strong enough vehicle-bridge interaction response. On the other hand, if the speed is too high (e.g., highway speeds), the vehicle travelling time may be too short for the bridge to go through a full cycle of vibration [13,19]. Another concern is that too-different velocities would excite distinct modes of the bridge, and thus affecting the detection performance. The maximum speed of the vehicle model is 0.9 m/s, and in the test, the maximum speed is used. An acceleration ramp is also used to ensure the speed can reach its max before entering the bridge.

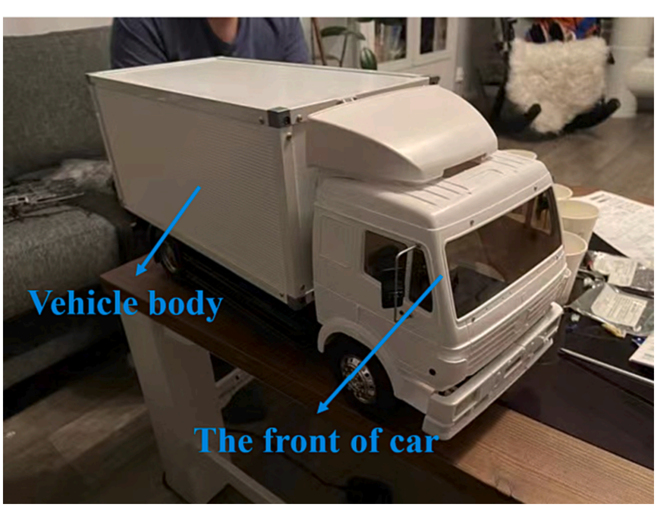
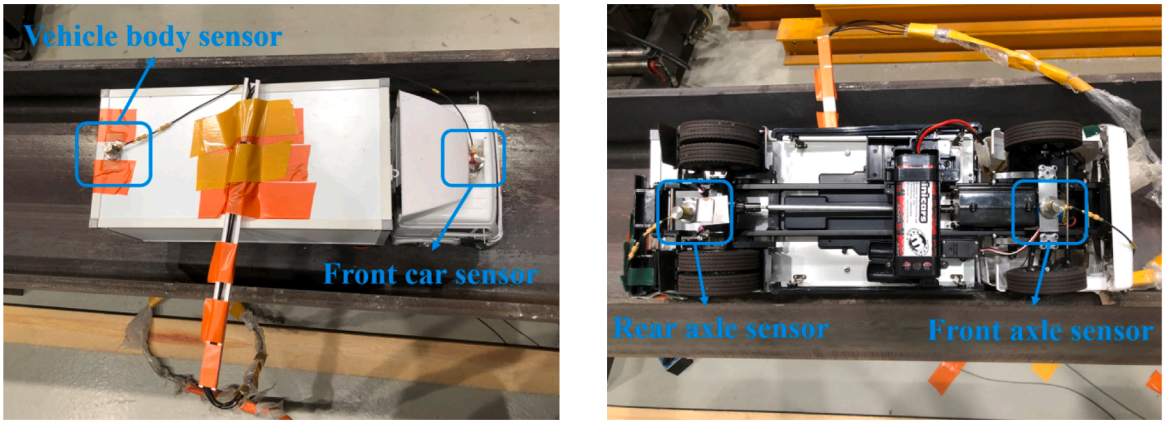


Fig. 9. Scale vehicle model.

3.3. Experimental method

The vehicle is driven across the beam in original condition with 6 kg weights applied on it to acquire a healthy case, which is referred to as "Case0". Other structural states are collected from 3 damage positions and 3 damage severities, where additional masses, m_s, are placed on 0.6 m (0.15L), 2 m (0.5L) and 2.4 m (0.6L), respectively, and masses vary from 5 kg (1 % structural mass increase) to 20 kg (4 % structural mass increase). 0.5L and 0.6L represent the damage locations at and near the



(a) (b)

Fig. 10. Sensor installation on the vehicle: (a) Bottom vehicle, (b) Top vehicle.

(a) (b) (c)

Fig. 11. Vehicle setup: (a) Weights inside the vehicle body, (b) Electric controller, (c) The vehicle on the beam.

Table 1
Health state description.

Case No.	Location	Weight	Case No.	Location	Weight
0	0	0 (Healthy)	3	0.6 m	5 kg (Small)
1	0.6 m	20 kg (Medium)	4	2 m	20 kg (Medium)
2	0.6 m	10 kg (Small)	5	2.4 m	20 kg (Medium)

mid-span of the bridge, and 0.15L stands for the damage location near the bridge support. The placement of mass at different locations is used to validate the viability of the method in cases 1, 4, and 5. Due to the larger vibration responses in the mid-span bridge, the detection performance of the mid-span is usually better than that near the support. 0.15L, as one of the most unfavorite location cases, is selected to explore the sensitivity of the method to the bridge damage by using different mass sizes (cases 1–3). The description of these health states is shown in Table 1. Each state contains 200 vehicle passages, building the dataset for damage diagnosis. Thus, there are 200 (runs) $\times$ 6 (cases) $\times$ 7 (sensors) = 8400 (signals), and each signal has 8000 discrete points corresponding to 4 s of “valid acceleration segments”.

By borrowing the renowned sociological concept of “negative population growth”, common structural damages like cracks and corrosion that reduce the local stiffness and mass can be referred to as positive structural damages, while negative structural damage is manually generated by increasing the local structural stiffness and mass. As with positive structural damages, the “negative structural damage” will also cause changes in bridge dynamic properties (e.g., natural frequency). For example, the first mode natural frequency of the beam, f_{b1}, with the additional masses of 4 % and 1 % at the mid-span, can be approximated as 34.07 Hz (3.77 % frequency change) and 35.06 Hz (0.99 % frequency change), respectively, according to the formular derived by Liu et al. [30]. Mass increases will lead to mode frequency changes, but more than that, they will change the amplitudes in both time-domain and frequency-domain responses [30]. It is possible to detect small-scale damage (less than 2 % of structural change) in the laboratory environment.

4. Results and analysis

The proposed methodology is compared with commonly used classification algorithms such as Linear-SVM, RBF-SVM, Artificial Neural Network (ANN), Gaussian Process (GP), Random Forest (RF) and Quadratic Discriminant Analysis (QDA) to demonstrate its good performance in damage indication. Then, the influence of C values and the algorithm’s boosting mechanism are discussed based on experimental samples. Diagnostic performances of vehicle sensors in different locations are discussed and compared with bridge sensors to show the high efficiency of the designed SHM framework.

4.1. Evaluation of damage diagnosis performance

At a ratio of 85 %: 15 %, the dataset is partitioned into training and

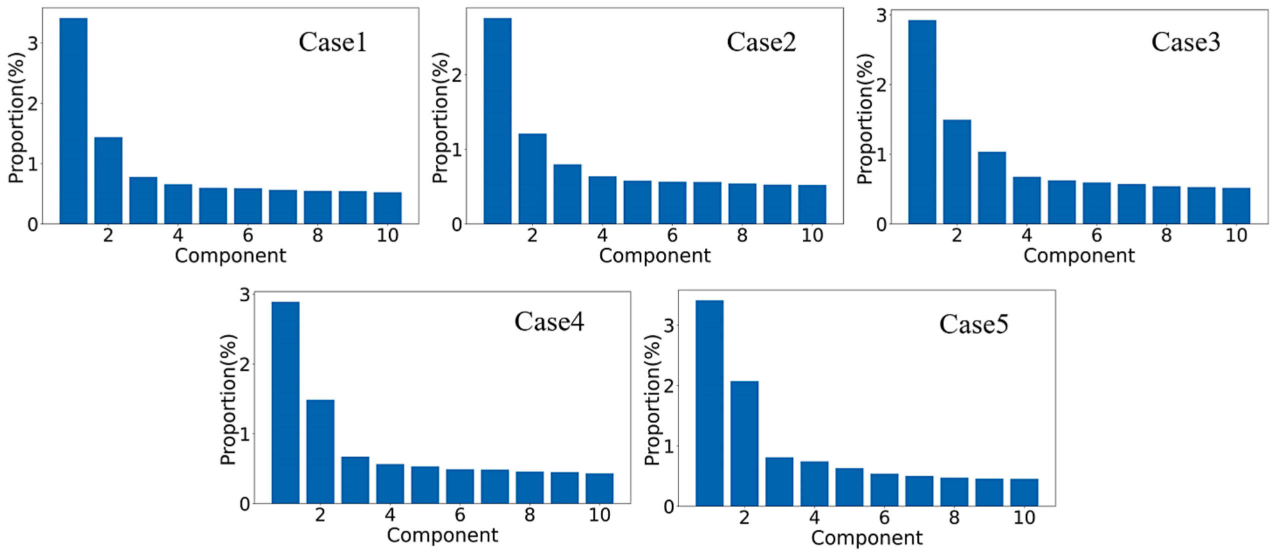


Fig. 12. Proportions of explained variance of the first 10 PCs.

Table 2
Major parameters of classification algorithms.

Algorithm	Configuration	Algorithm	Configuration
Linear-SVM	C = 5	GP	Kernel = 10 * RBF (10)
RBF-SVM	gamma = 0.01, C = 5	RF	n_estimators = 1000, max_features = 20
ANN	hidden_layer_sizes=(10, 4), alpha = 1, max_iter = 1000	QDA	reg_param = 0

testing subsets, and the overall performance of each algorithm is assessed via 5-fold cross validations. The results from the rear axle sensor are illustrated herein, while results from sensors on other positions will be discussed later. In this study, the vertical vehicle accelerations are used as direct inputs, and PCA method as a dimensionality reduction tool is only used to visualize the classification results. PCA converts a given dataset into a new coordinate system by employing an orthogonal linear transformation [51]. As shown in Fig. 12, the first principal component (feature 1) has the largest variance, followed by the second principal component (feature 2), and so on. The first two features are used to visualize the classification results.

The performance of the proposed algorithm is demonstrated by comparing with six commonly used classification algorithms, and their main parameters are determined by Grid Search [52] as presented in Table 2. Grid Search finds the optimal parameters by evaluating all the possible combinations of parameter values in the lists, with the combination that yields the highest cross validation score being retained. Parameter lists for Gird Search are: C: [0.1, 0.2, 0.3, …, 10] for Linear-SVM; Gamma: [0.05, 0.1, 0.15, …, 2], C: [0.1, 0.2, 0.3, …, 10] for RBF-SVM; Hidden_layer_sizes: [(1, 1), (1, 2), (1, 3), …, (1, 20), (2, 1), (2, 2), …, (20, 20)], alpha: [0.001, 0.01, 0.1, 1, 10], max_iter: [10, 100, 1000] for ANN; Kernel: [0.5 * RBF(0.5), 0.5 * RBF(1.0), 0.5 * RBF(1.5), …, 20 * RBF(20)] for GP; N_estimators: [20, 40, 60, …, 1000], max_features: [2, 4, 6, …, 100] for RF; reg_param: [0, 0.1, 0.2, …, 10] for QDA. For parameter combinations with the same scores, the optimum configurations are manually selected from one of those. While the performance of QDA seems to be poor for all parameter selections (close to 50 %), and its configuration is set to default (reg_param = 0). ANNs could contain very complex structures and parameters, for which finding an optimal or unique solution towards the given dataset would be difficult and somewhat beyond the scope of this paper. As a result, only ANNs with simple structures are investigated to obtain comparative results.

In Table 3, the classification performance of 5 damage scenarios illustrate that the proposed methodology outperforms other algorithms by better distinguishing vibration samples and giving higher result accuracies. It is found that Linear SVM may be more suitable for this type of problem, providing generally good performance on the given dataset, as the previous thought that linear and simple classifiers can separate the high-dimensional spaces easily. The present strategy further boosts its performance by learning from misclassified samples on the basis of Linear SVM. Optimized AdaBoost-Linear SVM (OAB-Linear SVM) increases the accuracy by 6.4 % on average when compared to the linear SVM. Meanwhile, QDA appears to perform similarly to a random guess in all the cases, which indicates that QDA may not be suitable as a classifier for high-dimensional vibration signals. Excluding the results of QDA, the proposed algorithm can effectively improve the result accuracy on all cases by 5 % to 16.7 %, when compared to other algorithms. The PCA visualization results of the first two features for Case1 are presented in Fig. 13, corresponding to the largest damage severity. The larger damage seems to have a more evident clustering of structural states than the minor damage, by which the classifier can divide the data points into two groups more easily. This will be more apparent in higher-dimensional spaces, as the first two components can only reveal a portion of the health state information. A more detailed discussion of the accuracy and the classification mechanism will be provided in Section 4.2.

AdaBoost forces the linear SVMs as component classifiers to concentrate on misclassified samples from the minority class, avoiding

Table 3
Classification performance for different algorithms.

Case No.	Details	**OAB-Linear SVM**	Linear-SVM	RBF-SVM	GP	ANN	RF	QDA
Case1	0,15L, 20 kg	**85.0 %**	78.3 %	68.3 %	73.3 %	76.7 %	76.7 %	45.0 %
Case2	0,15L, 10 kg	**83.3 %**	75.0 %	68.3 %	66.7 %	71.7 %	70.0 %	51.7 %
Case3	0,15L, 5 kg	**78.3 %**	73.3 %	66.7 %	66.7 %	71.7 %	66.7 %	53.3 %
Case4	0,5L, 20 kg	**88.3 %**	83.3 %	71.7 %	81.7 %	81.7 %	81.7 %	56.7 %
Case5	0,6L, 20 kg	**88.3 %**	81.7 %	73.3 %	78.3 %	81.7 %	83.3 %	50.0 %

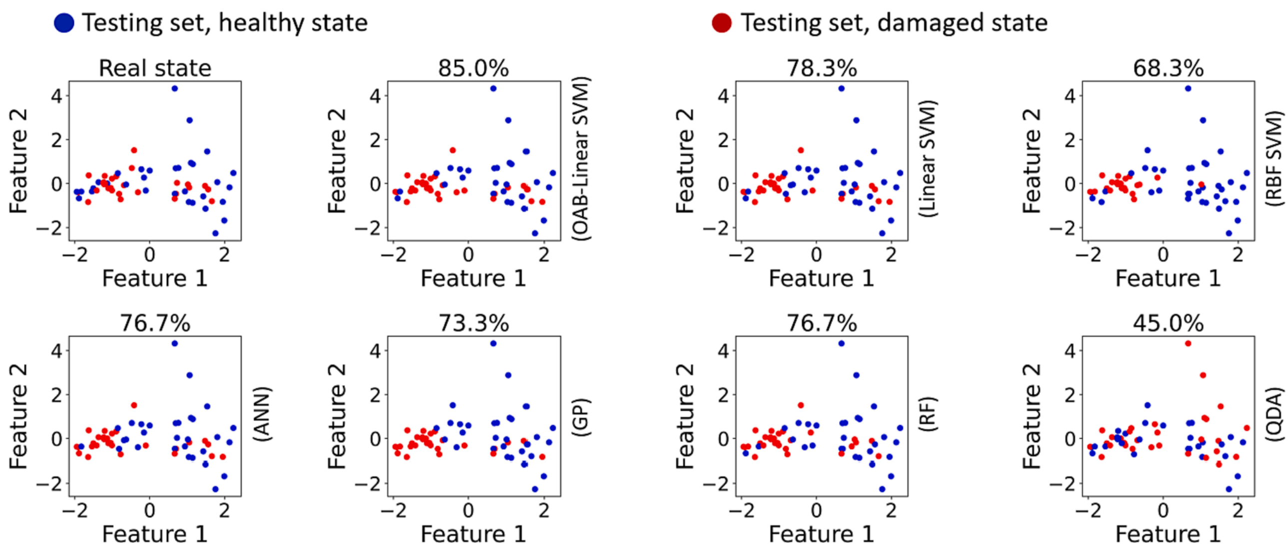


Fig. 13. Classification results of Case1.

the minor damage features from being considered as noises, which is the key to improving the accuracy of detection results. On the one hand, such a mechanism makes the algorithm more sensitive to the damage, but on the other hand, a concern is that when the noise is more dominant than the damage feature, the algorithm may focus on the noise instead of the damage feature [53]; there may be a need to ensure that the noise is less dominant than the small damage features. It is found experimentally that when the mass increase is greater than 5 kg (1 %), the noise is less likely to mask the damage features, for which the algorithm is effective. In some previous studies, the modal frequency or several features extracted from the frequency domain are used as the input, but they can only represent a portion of the health state information, which can be referred to in the PCA plots in the paper (see Fig. 12); this could lead to a loss of information related to the damage, especially for the small-scale damage. Some researchers suggest that the time-domain signal contains richer damage information and is more sensitive to structural damage (especially small/local damage) [54–56]. This paper uses the entire time-domain signal as input, which can provide the algorithm with more knowledge related to the damage. Therefore, compared to some previous methodologies, the proposed approach framework can achieve improved performance and is more sensitive to small damage.

To further show the superior performance of the present algorithm, Table 4 provides the comparison results for different algorithms integrated with AdaBoost: proposed Optimized AdaBoost-Linear SVM (OAB-Linear SVM), AdaBoost with Linear SVM component classifiers (AB-Linear SVM), AdaBoost with RBF SVM component classifiers (AB-RBF SVM), AdaBoost with Random Forest component classifiers (AB-RF) and AdaBoost with Neural Networks component classifiers (AB-ANN). Not all the algorithms can be boosted with AdaBoost, where the classifiers used as component learners in AdaBoost need to support sample weights, according to Freund and Schapire [57]. Gaussian Process (GP) and Quadratic Discriminant Analysis (QDA) cannot be employed as effective base learners for AdaBoost. For OAB-Linear SVM, the hyper-parameters of AB-Linear SVM are tuned by the proposed optimization method, while the parameters of AB-Linear SVM, AB-RBF SVM, AB-RF and AB-ANN are determined by Random Search [58], one of the most effective Hyper-Parameter Optimization tools. All computations in this study were executed in Python 3.8 64-bits on Windows using scikit-learn and SciPy packages [59,60], on a laptop PC with AMD Ryzen 7 CPUs and 8 GB RAM. OAB-Linear SVM outperforms other algorithms with Ada-Boost in almost all the cases, providing higher accuracy. AdaBoost cannot boost a classifier very efficiently without fine-tuned configurations, since AdaBoost as a traditional "moderate-classifier booster" has strict principles for its component classifiers. The optimal parameters of the classifier itself are usually not the optimal for AdaBoost. The proposed OAB-Linear SVM has a higher average improvement (Avg. imp.) than others, which can demonstrate the high efficiency of the present parameter optimization strategy. Meanwhile, it has been shown that the computational efficiency of AB-SVMs is higher than that of AB-RF and AB-ANN, with less average running time (Avg. time). Among them, the computing resources used by AB-ANN are over ten times those of AB-SVMs, so the combination of AdaBoost and complex algorithms should be avoided if possible.

Due to the time and expense restraints, field or laboratory test data might be limited in some cases, and thus there is a need to investigate the algorithm's performance regarding the data amount. The sample size mentioned below refers to the size of the health data (baseline). From Fig. 14, it is found that along with the increasing samples for tests, the accuracies of OAB-Linear SVM and Linear SVM rise synchronously in the largest damage case, where similar trends can be seen in other damage cases. OAB Linear-SVM overperforms Linear-SVM with higher accuracy at all sample sizes, and more than that, it exhibits a relatively smooth and steady climbing trend. In the case of the medium damage (4 % mass increase), the accuracy of OAB Linear-SVM reaches 66.7 % (50 % for

Table 4
Comparison results for different algorithms integrated with AdaBoost.

Case No.	Details	**OAB-Linear SVM**	AB-Linear SVM	AB-RBF SVM	AB-RF	AB-ANN
Case1	0,15L, 20 kg	**85.0 %**	78.3 %	71.7 %	78.3 %	80.0 %
Case2	0,15L, 10 kg	**83.3 %**	78.3 %	71.7 %	73.3 %	75.0 %
Case3	0,15L, 5 kg	**78.3 %**	78.3 %	70.0 %	70.0 %	73.3 %
Case4	0,5L, 20 kg	**88.3 %**	85.0 %	76.7 %	85.0 %	83.3 %
Case5	0,6L, 20 kg	**88.3 %**	85.0 %	76.7 %	85.0 %	83.3 %
Avg. imp.		**6.4 %**	2.7 %	3.7 %	2.7 %	2.3 %
Avg. time		22.6 s	**18.3 s**	20.6 s	31.2 s	293.5 s

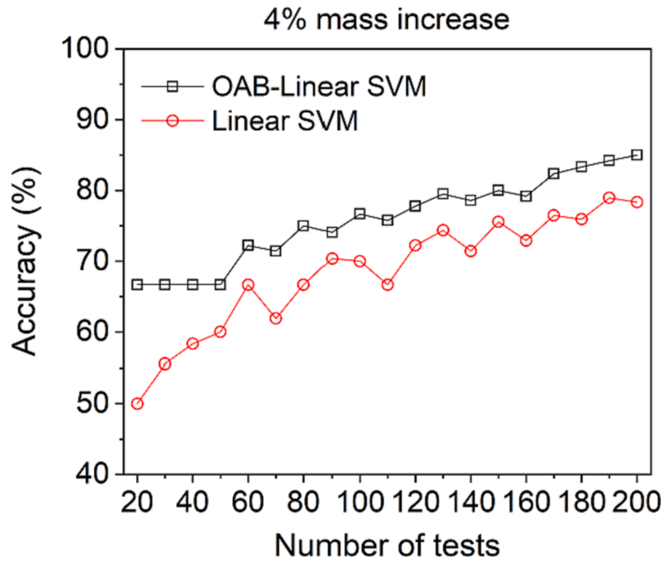


Fig. 14. Comparison results on various-sized tests.

Linear SVM), even though there are only 20 samples available. Evidently, the merits of this algorithm make it possible to achieve a satisfactory result accuracy when there are limited amounts of data.

4.2. Discussion on the mechanisms

Section 4.1 validates the outstanding performance of OAB-Linear SVM in structural damage detection. It is also important to understand the boosting mechanisms of the proposed method. This section will discuss: (1) how the optimizing program seeks the optimal performance of AB-Linear SVM by adjusting the regularization parameter, C; (2) how the boosting mechanism functions to improve the result accuracies.

Fig. 15 shows the result accuracies on 9 damage scenarios with varied C values. The performance of AB-Linear SVM appears to be sensitive to the C values. The algorithm just becomes a Linear SVM with the same accuracy, when the value of C is too large. While the AdaBoost mechanism cannot give effective accuracy improvement when the value of C is too small or improper. The C parameter informs the SVM optimizer how much it should avoid misclassification on each training example. For large C values, a smaller margin hyperplane will be chosen by the SVM optimizer if it performs better of correctly classifying all the training points. A small C value, on the other hand, will cause the optimizer to seek a larger margin separating hyperplane, even if it misclassifies more points. A medium and appropriate C parameter is critical to the AdaBoost's function in improving the result accuracy, as it cannot learn from a classifier that is too strong or too weak. For this case study, the C value lies in the rough range of 3.2 to 13, while for other cases it can be determined by the proposed optimization strategy.

For a valid C value, the generalization performance of AB-Linear SVM is boosted through numerous iterations. Fig. 16 shows the comparative results on five cases of different health states with varied boosting cycles over a large range (5 iteration increments as one point in the figure). Despite some fluctuation, the test accuracy climbs as the iteration increases until it reaches the maximum score on testing sets, after which the accuracy remains stable. This indicate that large iteration numbers can be advantageous to improve the generalization performance, but it also requires a higher computational cost. Fig. 17 illustrates the classification results of Case1 on testing sets corresponding to diverse iteration numbers, which represent the largest damage case. Through the "extra knowledge" learned from the mistaken

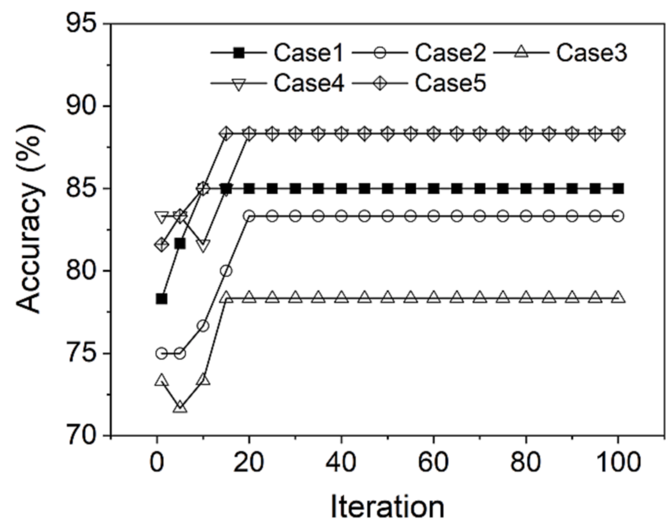


Fig. 16. Performance of OAB-Linear SVM with different boosting iterations.

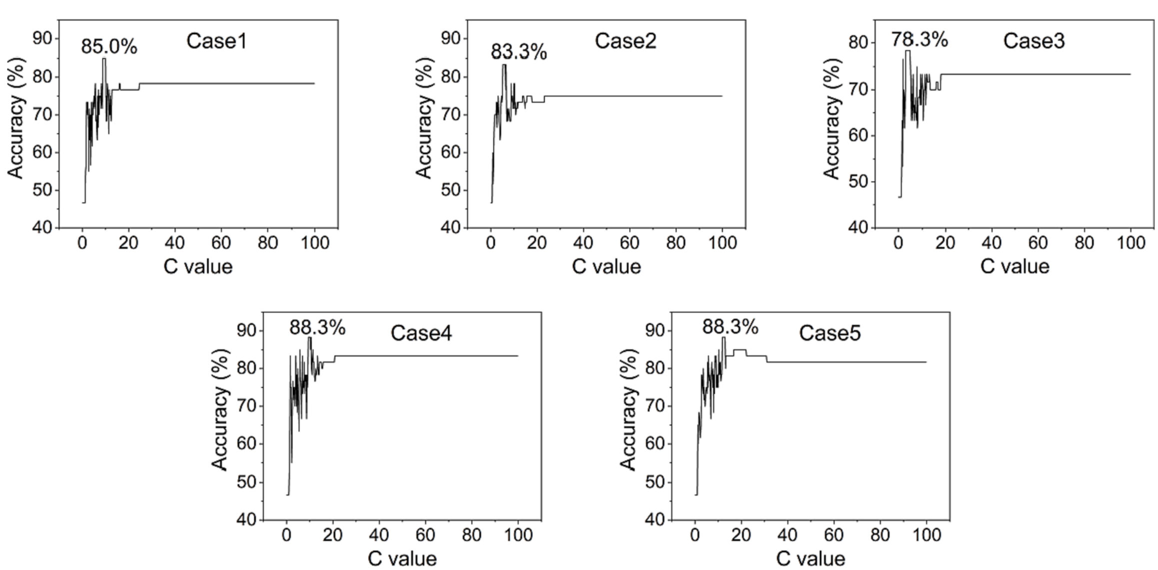


Fig. 15. Performance of AB-Linear SVM with different C values for different damage cases.

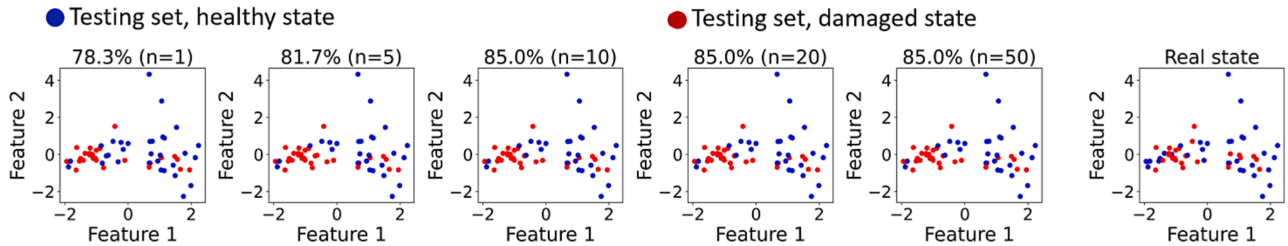


Fig. 17. Classification results of OAB-Linear SVM with different boosting iterations for Case1.

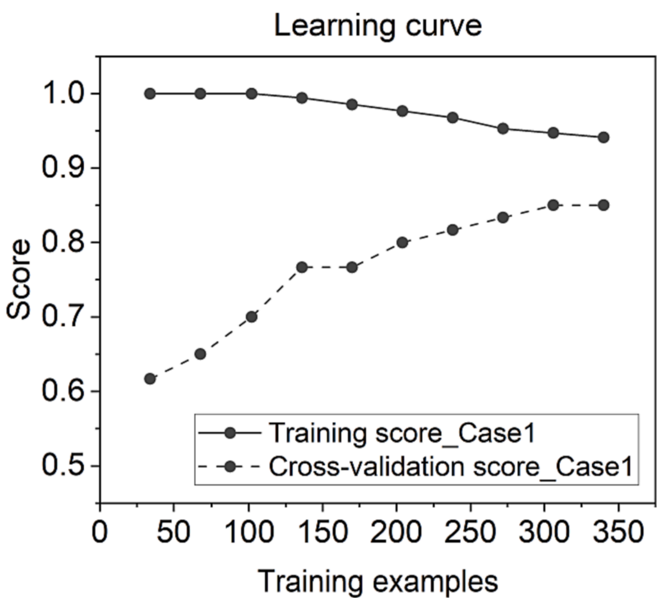


Fig. 18. Learning curves of OAB-Linear SVM for Case1.

samples, the boosting mechanism corrects some misclassified points through multiple iterations, thereby improving the result accuracy. After achieving a certain performance, the boosting mechanism can no longer enhance the accuracy from the iteration process, which often means that the linear SVM as a component learner has hit its limit.

Fig. 18 shows the learning curves of OAB-Linear SVM for Case1, and similar trends can be observed in other cases. Such curve shapes can be found in complex databases very often: the training score is very high at the beginning due to severe overfitting and declines gradually, whereas the cross-validation score is low at the beginning and rises. The validation score could be increased with more training samples. Table 5 presents the results of precision, recall, and accuracy for different damage cases. In each case, the precision, recall, and accuracy are evidently higher than 50 % (random guess), which statistically justify the effectiveness of the proposed method. The precision, recall, and accuracy tend to decline as the damage level decreases.

4.3. Performance comparison for different sensor locations

The above results are obtained from the vehicle sensor on the rear axle, and diagnosis results for different sensor locations are shown as Table 6. Results from the bridge sensors are employed for the comparison of direct and indirect methods regarding to the accuracy. There is no significant difference in the classification accuracy for each sensor location except the front car. This is because, as shown in Fig. 19, the rails are used to guide the vehicle to be driven straightly in the experiment, where the contact between the guide rail and the front car limits the front car's free vibration. The acceleration signals from the front car do not truly reflect the bridge vibration, and in this case, the front car signals are regarded as unavailable. The similarity of the classification results from sensors on the vehicle and on the bridge implies that the indirect SHM framework utilizing a passing vehicle is equally effective as the direct SHM system. Meanwhile, the present strategy's performance is not restricted to specific SHM frameworks or sensor locations. Furthermore, in the medium damage cases (e.g., cases 4, 5), the

Fig. 19. Contact between the front car and the rail.

Table 5
Results of precision, recall and accuracy.

Case No.	Details	precision	recall	accuracy
Case1	0,15L, 20 kg	82.76 %	85.71 %	85.00 %
Case2	0,15L, 10 kg	78.79 %	89.66 %	83.33 %
Case3	0,15L, 5 kg	74.19 %	82.14 %	78.33 %
Case4	0,5L, 20 kg	88.46 %	85.19 %	88.33 %
Case5	0,6L, 20 kg	92.00 %	82.14 %	88.33 %

Table 6
Diagnosis results for diverse sensor locations.

Case No.	Details	Car body	Rear axle	Front axle	Front car	Beam1	Beam2	Beam3
Case1	0,15L, 20 kg	85.0 %	85.0 %	83.3 %	46.7 %	85.0 %	85.0 %	85.0 %
Case2	0,15L, 10 kg	81.6 %	83.3 %	83.3 %	46.7 %	83.3 %	83.3 %	83.3 %
Case3	0,15L, 5 kg	78.3 %	78.3 %	78.3 %	46.7 %	78.3 %	78.3 %	78.3 %
Case4	0,5L, 20 kg	88.3 %	88.3 %	85.0 %	46.7 %	90.0 %	90.0 %	90.0 %
Case5	0,6L, 20 kg	86.6 %	88.3 %	86.6 %	46.7 %	88.3 %	88.3 %	88.3 %

proposed methodology can reach an identification accuracy of nearly 90 % even though there are only 200 cases available, which is often required for thousands of training cases in previous methods. Improving the identification performance by appropriate algorithms can increase the efficiency in data utilization and probably reduce the costs in data collection.

5. Conclusion

An Optimized AdaBoost-Linear SVM algorithm is proposed in this paper to indicate the occurrence of bridge damages utilizing the raw vehicle acceleration signals. Well-designed linear SVMs by an optimization strategy are used as component classifiers in AdaBoost, where the C value is adaptively modified to seek the optimal generalization performance of the algorithm. The present model has been validated via the dataset received by the laboratorial experiments, where a steel beam and a scale truck model with an engine are used. Additional weights on the beam of different sizes and positions are used to simulate damage scenarios. Based on the experimental results, the following conclusions can be drawn:

(1) The proposed optimization strategy can find the optimal C value for the linear SVM, enabling it to be the effective component learner in AdaBoost, which provides the improved generalization performance for damage detection. The configuration of AdaBoost-Linear SVM is determined automatically with the dataset, and this provides the potential to automate the health state identification process and achieve real-time SHM systems in the future.

(2) The proposed Optimized AdaBoost-Linear SVM, is demonstrated to have better performance than other methods that are commonly used in classification problems, such as RBF SVM and Random Forest, with improvements ranging from 5 % to 16.7 %. Compared with the linear SVM, the proposed algorithm boosts the accuracy by 6.4 % on average. These advantages could allow it to become a preferable option for health state identification problems.

(3) The boosting mechanism in the algorithm makes it sensitive to the damage. The proposed algorithm remains a good result accuracy of 78.3 % for the small damage (1 % mass increase). It could expand the lower limit of the detectable damage range and is of great significance for the detection of minor damages.

(4) Similar and high identification accuracies are seen in sensors at diverse locations on both the vehicle and the bridge when applying the present approach. According to these results, the vehicle-based indirect SHM framework can be equally effective as the direct SHM systems, and the proposed algorithm is not strictly limited to specific sensor locations or SHM frameworks.

Future work will target the limitations of the proposed diagnosis algorithm for indirect bridge health monitoring. Firstly, experiments were conducted with a single-configuration vehicle in a normal laboratory environment, where white noise and motor noise are the major noise components in the experiment. It is necessary to verify the present model's robustness under more realistic and complex conditions involving vehicle parameter variations (weight, speed, etc.), environmental influences and road profile effects. Secondly, the proposed approach framework can successfully detect the existence of minor damage, but the detection of damage locations and severities still needs further research. A frontier of research is the integration of the proposed methodology with semi-supervised or unsupervised learning methods to build a new generation of smart bridges for health monitoring that is capable of accurately detecting damage existence, locations, severities, etc. Lastly, as a data-driven model, its physical explanation deserves further study.

CRediT authorship contribution statement

Yifu Lan: Conceptualization, Methodology, Investigation, Writing – original draft, Visualization. **Youqi Zhang:** Funding acquisition, Supervision, Writing – review & editing. **Weiwei Lin:** Funding acquisition, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Some or all data that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments

This research was fully sponsored by the Jane and Aatos Erkko Foundation in Finland (Grant No. 210018). The 1st author was also financially supported by the Finnish Foundation for Technology Promotion (TES) and Chinese Scholarship Council (CSC). The second author was funded by the Academy of Finland Postdoctoral Research Project (339493). The financial support and the assistance of the laboratory staff at Aalto university are gratefully acknowledged. Any findings, opinions, conclusions, and recommendations of this paper are those of the authors and do not necessarily reflect the views of the research sponsor.

References

[1] Lin W, Taniguchi N, Yoda T. Novel method for retrofitting superstructures and piers in aged steel railway bridges. J Bridge Eng 2017;22(11):05017009.
[2] Davis SL, Goldberg D. The Fix We're In For: The State of Our Nation's Bridges 2013. Washington: DC, USA; 2013.
[3] Znidaric A, Pakrashi V, O'Brien E, O'Connor A. A review of road structure data in six European countries. Proc ICE: Urban Des Plan 2011;164(4):225–32.
[4] Rashidi M, Lemass BP. A decision support methodology for remediation planning of concrete bridges 2011.
[5] Fujino Y, Siringoringo DM. Bridge monitoring in japan: the needs and strategies. Struct Infrastruct Eng 2011;7(7-8):597–611.
[6] Mattioli, G. The Guardian, UK 2019; viewed 22 March 2022, <https://www.theguardian.com/cities/2019/feb/26/what-caused-the-genoa-morandi-bridge-collapse-and-the-end-of-an-italian-national-myth>.
[7] Sohn H, Farrar CR, Hemez FM, Shunk DD, Stinemates DW, Nadler BR, et al. A review of structural health monitoring literature: 1996–2001. USA: Los Alamos National Laboratory; 2003.
[8] Enckell M, Glisic B, Myrvoll F, Bergstrand B. Evaluation of a large-scale bridge strain, temperature and crack monitoring with distributed fibre optic sensors. J Civil Struct Health Monit 2011;1(2):37–46.
[9] Kim S, Pakzad S, Culler D, Demmel J, Fenves G, Glaser S, Turon M. Wireless sensor networks for structural health monitoring. Proceedings of the 4th international conference on Embedded networked sensor systems, ACM 2006; 427–428.
[10] Elhattab A, Uddin N, O'Brien E. Drive-by bridge damage monitoring using bridge displacement profile difference. J Civil Struct Health Monitor 2016;6(5):839–50.
[11] Malekjafarian A, McGetrick P, O'Brien E. A review of indirect bridge monitoring using passing vehicles. Shock Vib 2015;2015:1–16.
[12] Yang Y, Lin C, Yau J. Extracting bridge frequencies from the dynamic response of a passing vehicle. J Sound Vib 2004;272(3–5):471–93.
[13] Hester D, González A. A discussion on the merits and limitations of using drive-by monitoring to detect localised damage in a bridge. Mech Syst Sig Process 2017;90:234–53.
[14] Lin C, Yang Y. Use of a passing vehicle to scan the fundamental bridge frequencies: an experimental verification. Eng Struct 2005;27(13):1865–78.
[15] Yang Y, Li Y, Chang K. Constructing the mode shapes of a bridge from a passing vehicle: a theoretical study. Smart Struct Syst 2014;13(5):797–819.
[16] Malekjafarian A, Obrien EJ. Identification of bridge mode shapes using short time frequency domain decomposition of the responses measured in a passing vehicle. Eng Struct 2014;81:386–97.
[17] Lan Y, Lin W, Zhang Y. Bridge frequency identification using multiple sensor responses of an ordinary vehicle. Int J Struct Stab Dyn 2022;2350056.
[18] Obrien EJ, Malekjafarian A. A mode shape-based damage detection approach using laser measurement from a vehicle crossing a simply supported bridge. Struct Control Health Monit 2016;23(10):1273–86.
[19] Yang YB, Yang JP. State-of-the-art review on modal identification and damage detection of bridges by moving test vehicles. Int J Struct Stab Dyn 2018;18(2):1850025.
[20] Cantero D, McGetrick P, Kim CW, O'Brien E. Experimental monitoring of bridge frequency evolution during the passage of vehicles with different suspension properties. Eng Struct 2019;187:209–19.

[21] Kim CW, Isemoto R, McGetrick PJ, Kawatani M, OBrien EJ. Drive-by bridge inspection from three different approaches. Smart Structures and Systems 2014; 5: 775-796.
[22] Spiridonakos MD, Chatzi EN, Sudret B. Polynomial chaos expansion models for the monitoring of structures under operational variability. ASCE-ASME J Risk Uncertainty Eng Syst, Part A: Civ Eng 2016;2(3):B4016003.
[23] Zhang Y, Miyamori Y, Kadota T, Saito T. Investigation of seasonal variations of dynamic characteristics of a concrete bridge by employing a wireless acceleration sensor network system. Sens Mater 2017;29(2):165–78.
[24] Zhang Y, Miyamori Y, Mikami S, Saito T. Vibration-based structural state identification by a 1-dimensional convolutional neural network. Comput-Aided Civ Infrastruct Eng 2019;34(9):822–39.
[25] Miyamoto A, Yabe A. Development of practical health monitoring system for short- and medium-span bridges based on vibration responses of city bus. J Civil Struct Health Monit 2012;2:47–63.
[26] OBrien EJ, McGetrick PJ, Gonzalez A. A drive-by inspection system via vehicle moving force identification. Smart Struct. Syst. 2014; 13(5): 821–848.
[27] Obrien EJ, Keenahan J. Drive-by damage detection in bridges using the apparent profile. Struct Control Health Monit 2015;22(5):813–25.
[28] Lan Y. Improving the Drive-by bridge inspection performance by vehicle parameter optimization. Proceedings of 8th Asia Pacific Workshop on Structural Health Monitoring (8AMWSHM) 2021; 18: 195-202.
[29] Zhang Y, Miyamori Y, Saito T, Mikami S, Oshima T. Robustness Tests of a Vibration-based Structural State Identification Method Through a 1-D Convolutional Neural Network. Proceedings of 9th International Conference on Structural Health Monitoring of Intelligent Infrastructure Conference (SHMII9), Missouri, USA, August 2019.
[30] Liu J, Chen S, Bielak J, Garrett JH. Diagnosis algorithms for indirect structural health monitoring of a bridge model via dimensionality reduction. Mech Syst Sig Process 2020;136:106454.
[31] Alamdari MM, Rakotoarivelo T, Khoa NLD. A spectral-based clustering for structural health monitoring of the Sydney Harbour Bridge. Mech Syst Sig Process 2017;87:384–400.
[32] Shu J, Plos M, Zandi K, Ashraf A. Distribution of shear force: a multi-level assessment of a cantilever RC slab. Eng Struct 2019;190:345–59.
[33] Shu J, Honfi D, Plos M, Zandi K, Magnusson J. Assessment of a cantilever bridge deck slab using multi-level assessment strategy and decision support framework. Eng Struct 2019;200:109666.
[34] McGovern A, Lagerquist R, John Gagne D, Jergensen GE, Elmore KL, Homeyer CR, et al. Making the black box more transparent: understanding the physical implications of machine learning. Bull Am Meteorol Soc 2019;100(11):2175–99.
[35] Chen K, Meng X. Interpretation and understanding in machine learning. J Comput Res Dev 2020;57(9):1971–86.
[36] Cerda F, Chen S, Bielak J, Garrett J, Rizzo P, Kovacevic J. Indirect structural health monitoring of a simplified laboratory-scale bridge model. Smart Struct Syst 2014; 13(5):849–68.
[37] Lederman G, Wang Z, Bielak J, Noh H, Garrett J, Chen S, Kovacevic J, Cerda F, Rizzo P. Damage quantification and localization algorithms for indirect SHM of bridges. Bridge Maintenance, Safety, Management and Life Extension, CRC Press 2014; 640–647.
[38] Malekjafarian A, Golpayegani F, Moloney C, Clarke S. A machine learning approach to bridge-damage detection using responses measured on a passing vehicle. Sensors 2019;19:4035.
[39] Tran-Ngoca H, Khatira S, De Roeckc G, Bui-Tienb T, Abdel WM. An efficient artificial neural network for damage detection in bridges and beam-like structures by improving training parameters using cuckoo search algorithm. Eng Struct 2019; 199:109637.
[40] Vapnik V. Statistical Learning Theory. New York: Wiley; 1998.
[41] Alamdari MM, Khoa NLD, Runcie P, Mustapha S, Dackermann U, Li J, Nguyen VV, Gu X. Application of unsupervised support vector machine for condition assessment of concrete structures. Proceedings of the Second International Conference on Performance-based and Life-cycle Structural Engineering (PLSE 2015), Brisbane, QLD, Australia: School of Civil Engineering, The University of Queensland; 2015, 182–189.
[42] Pan H, Azimi M, Gui G, Yan F, Lin Z. Vibration-based support vector machine for structural health monitoring. Exp Vibrat Anal Civil Struct 2018;5:167–78.
[43] Kuncheva LI, Whitaker CJ. Using diversity with three variants of boosting: aggressive conservative and inverse. In: Proceedings of the 3rd International Workshop on Multiple Classifier Systems 2002.
[44] Cheng WC, Jhan DM. A self-constructing cascade classifier with AdaBoost and SVM for pedestrian detection. Eng Appl Artif Intell 2013;26(3):1016–28.
[45] Zhang Y, Ni M, Zhang C, Liang S, Fang S, Li R, Tan Z. Research and Application of AdaBoost Algorithm Based on SVM. 2019 IEEE 8th Joint International Information Technology and Artificial Intelligence Conference (ITAIC) 2019; 662-666.
[46] Li X, Wang L, Sung E. AdaBoost with SVM-based component classifiers. Eng Appl Artif Intell 2008;21:785–95.
[47] Type 4371 Piezoelectric Charge Accelerometer | Brüel & Kjær n.d. https://www.bksv.com/en/transducers/vibration/accelerometers/charge/4371 (accessed October 2, 2022).
[48] Mei Q, Gül M, Marcus BM. Indirect health monitoring of bridges using Mel-frequency cepstral coefficients and principal component analysis. Mech Syst Sig Process 2019;119:523–46.
[49] Thorsen A, Lederman G, Oshima Y, Bielak J, Noh HY. Mitigating the effects of variable speed on drive-by infrastructure monitoring. Sens Smart Struct Technol Civil Mech Aerospace Syst 2015;9435:75–83.
[50] Makki Alamdari M, Chang KC, Kim CW, Kildashti K, Kalhori H. Transmissibility performance assessment for drive-by bridge inspection. Eng Struct 2021;242: 112485.
[51] Hastie T, Tibshirani R, Friedman J. The elements of statistical learning. 2nd ed. New York: Springer; 2009.
[52] LaValle SM, Branicky MS, Lindemann SR. On the relationship between classical grid search and probabilistic roadmaps. Int J Robot Res 2004;23(7–8):673–92.
[53] Dietterich TG. An experimental comparison of three methods for constructing ensembles of decision trees: bagging, boosting, and randomization. Mach Learn 2000;40:139–57.
[54] Alves V, Cury A, Roitman N, Magluta C, Cremona C. Structural modification assessment using supervised learning methods applied to vibration data. Eng Struct 2015;99:439–48.
[55] Santos JP, Cremona C, Orcesi AD, Silveira P. Early damage detection based on pattern recognition and data fusion. J Struct Eng 2017;143:04016162.
[56] de Almeida CR, Cury A, Barbosa F. Automated real-time damage detection strategy using raw dynamic measurements. Eng Struct 2019;196:109364.
[57] Freund Y, Schapire RE. A decision-theoretic generalization of on-line learning and an application to boosting. J Comput Syst Sci 1997;55(1):119–39.
[58] Bergstra J, Bengio Y. Random search for hyper-parameter optimization. J Mach Learn Res 2012;13:281–305.
[59] Pedregosa F, Varoquaux G, Gramfort A, Michel V, Thirion B, Grisel O, et al. Scikit-learn: machine learning in python. J Mach Learn Res 2011;12(2825):2830.
[60] Virtanen P, Gommers R, Oliphant TE, Haberland M, Reddy T, Cournapeau D, et al. SciPy 1.0: fundamental algorithms for scientific computing in python. Nat Methods 2020;17:261–72.