Chapter 13
Bridge Health Monitoring Using Vehicle-Mounted Sensors and Machine Learning Classification

Burak Duran, Saeed Eftekhar Azam, and Daniel G. Linzell

Abstract This work presents a novel framework for bridge structural health monitoring (SHM) by integrating indirect drive-by sensing with a 1D Convolutional Neural Network (CNN) model. In a full-scale field study, a reinforced concrete (RC) bridge in Nebraska was subjected to a series of controlled, progressive damage scenarios: an initial healthy state (D0), a localized parapet saw-cut (D1), simulated scour (D2), and deck keyway damage (D3). A U-Haul truck equipped with five accelerometers gathered vibration data while traversing the bridge at varying speeds (0-30 mph), replicating authentic traffic conditions. The collected time-series data were preprocessed and fed into a custom-designed 1D CNN for damage detection and classification. The model achieved a training accuracy of 99.9%, a validation accuracy of 94.44%, and a testing accuracy of 93%. A detailed examination of the confusion matrix indicated high diagnostic precision across all four damage states, with the healthy (D0) and most severe damage (D3) conditions classified with over 95% accuracy, scour (D2) with over 92% accuracy, and the subtle parapet damage (D1) with a robust performance above 85%. This research marks a significant step forward by successfully applying a 1D CNN to raw drive-by data from a full-scale, in-situ bridge, providing a strong proof-of-concept for a non-intrusive, scalable alternative to traditional SHM techniques.

Keywords Drive-by sensing · Convolutional neural networks · Full-scale bridge testing · Intelligent transportation systems · Damage detection

Introduction

Bridges are essential infrastructure, but their aging condition poses a growing global concern. In the U.S. alone, a substantial portion of the bridge inventory is approaching or has exceeded its design life, necessitating more proactive maintenance and monitoring strategies [1, 2]. Traditional SHM methods, such as visual inspections and periodic non-destructive testing (NDT), are often labor-intensive, time-consuming, and difficult to scale across a large number of bridges. Although vibration-based methodologies have shown potential in detecting stiffness change and structural degradation, they typically require extensive sensor deployments and introduce challenges associated with operational and environmental variabilities and measurement uncertainties.

Drive-by sensing has emerged as an innovative alternative, using instrumented vehicles as mobile platforms to indirectly assess bridge health [3, 4]. This approach offers significant advantages in cost-effectiveness, safety, and scalability. However, its practical implementation faces a primary challenge: the vehicle's dynamic response, coupled with road roughness and ambient environmental noise, can heavily contaminate the measured signals, masking the subtle signatures of structural damage.

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), are well-suited to address this challenge due to their capacity for automated feature extraction from raw data. While CNNs have been applied to SHM, most of these studies have been confined to numerical models or small-scale laboratory experiments [5]. This work stands apart

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by demonstrating the efficacy of a 1D CNN framework using drive-by data from a full-scale, operational bridge under controlled, realistic cumulative damage scenarios. This foundational study aims to bridge the gap between idealized experimental validations and the complexities of practical large-scale deployments, thereby laying the groundwork for a truly scalable SHM solution.

Methodology

Experimental Setup

The study was conducted on an operational bridge, Bridge Q110, located in the southeast of Lincoln, Nebraska, US, a single-span prestressed and pre-tensioned concrete double-tee bridge. The Q110 bridge had two lanes with a width of 30 feet and a span length of 44 feet. Bridge views from the site are provided in (**Figure 1**)

(a) Overview of the bridge including parapets (b) Bottom view

Fig. 1 Bridge Q110 views

A prior state of the bridge was assumed to be healthy. Then, a sequence of systematically imposed three damage states was introduced: D0 (healthy), D1 (a localized saw-cut to the north parapet), D2 (excavation of soil around abutment piles to simulate scour), and D3 (saw-cuts to the keyways between the double-tee beams) (**Figure 2**). These scenarios were designed to replicate potential failures and deterioration that could arise under real-world operating conditions, thereby providing meaningful challenges for evaluating the proposed CNN-based SHM approach. This progressive approach created a comprehensive dataset reflecting progressive structural degradation.

(a) Parapet after saw-cut (D1) (b) Exposed pile scour detailed view (D2) (c) Shear key-way being saw-cut (D3)

Fig. 2 Visual comparison of damage states showing D1, D2, and D3

A 26-foot U-Haul truck served as the sensing platform, equipped with five accelerometers placed at the front axle, rear axle, front suspension, rear suspension, and center of gravity (**Figure 3**). The vehicle's total weight was approximately

21,300 lbs, and it traversed the bridge at speeds of 10, 20, and 30 mph. This extensive test matrix, consisting of over 1,000 live-load runs, generated a robust dataset of acceleration time-series signals sampled at 500 Hz.

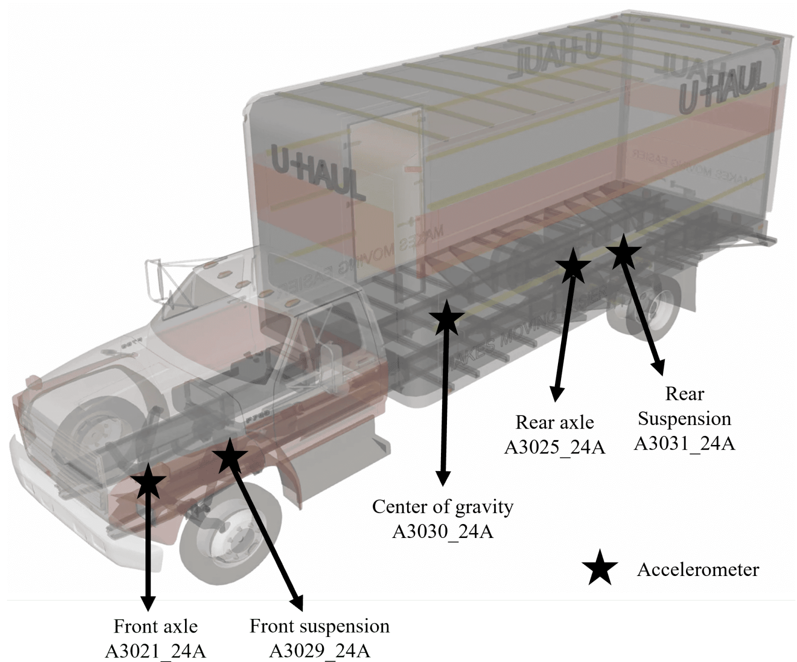

Fig. 3 Truck instrumentation plan and Accelerometer IDs

Data Preprocessing and Model Architecture

The raw acceleration signals, which varied in length, were resampled to a uniform length of 1500 data points using cubic interpolation. This method was chosen to provide a smooth approximation of the original signals while preserving key characteristics. The data were then normalized using a z-score standardization approach to feed the proposed CNN model.

The core of our framework is a custom 1D CNN model. The architecture was finalized through an iterative design and a grid search for hyperparameter optimization. The final network comprises four convolutional layers with increasing filter counts (64, 128, 256, 512), interspersed with max-pooling layers for dimensionality reduction. The network concludes with four fully-connected layers and a final SoftMax output layer for multiclass classification. The training was conducted over 200 epochs using the Adam optimizer on a dataset split into 70% training, 15% validation, and 15% testing subsets.

Results and Discussion

The 1D CNN model demonstrated an overall testing accuracy of 93%. A detailed analysis of the confusion matrix revealed robust per-class performance (**Figure 4**). The confusion matrix analysis of the 1D CNN model for Bridge Q110 demonstrates its overall effectiveness in classifying structural health states with high accuracy. For the healthy condition (D0), the model achieved a true positive rate of 95.3%, indicating strong capability in correctly identifying undamaged states and minimizing false alarms in structural health monitoring applications. In the case of north barrier damage (D1), the true positive rate was lower at 85.8%, suggesting that this damage type shares overlapping features with other states, which leads to a higher rate of misclassification and highlights the need for model refinement. For scour damage (D2), the model maintained a strong performance with a true positive rate of 92.3%, reflecting its effectiveness in detecting this critical form of deterioration that can significantly compromise bridge stability. The highest performance was observed for shear keyway damage (D3), with a true positive rate of 98.5%, demonstrating that this damage state has highly distinguishable characteristics that the model can reliably detect. Overall, the results confirm the model's strong capability in identifying both healthy and damaged conditions, with particularly high precision for scour and shear keyway damages, while also emphasizing the necessity of further improvements in differentiating north barrier damage from other states.

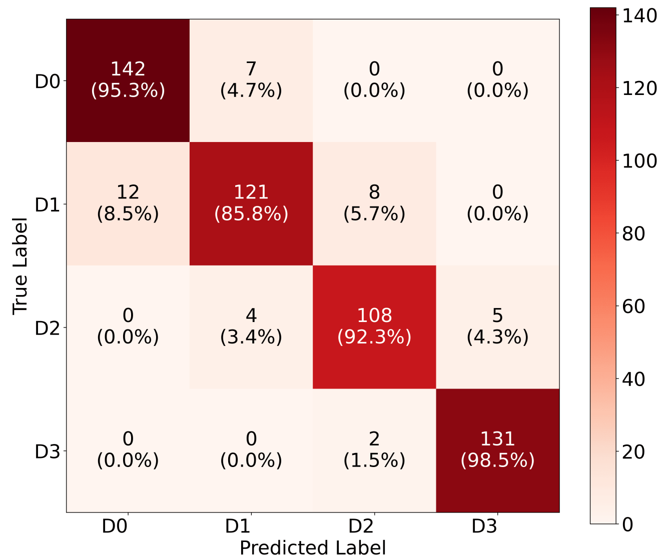

Fig. 4 Confusion matrix

Conclusion

This study offers a pioneering validation of a 1D CNN framework for drive-by sensing on a full-scale, operational bridge, accounting for diverse operational conditions, environmental variations, and measurement uncertainties. The findings demonstrate that the proposed methodology can reliably and accurately classify multiple cumulative damage states directly from raw, noise-contaminated acceleration data. Although the results are derived from a single bridge subjected to specific progressive damage scenarios and loading conditions, they highlight the potential of the 1D CNN framework to significantly advance bridge SHM by reducing dependence on costly, labor-intensive inspections.

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