Drive-by Damage Detection In Railway Bridges Using 1d Convolutional Neural Networks

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Abstract. The aging of civil engineering infrastructure emphasizes the importance of structural health monitoring (SHM) in railway bridges. Data-driven models are a prominent approach in this field. However, network-wide bridge instrumentation is logistically difficult and expensive, leading to the development of the drive-by or indirect monitoring method. In the drive-by approach, the instrumented vehicle acts as the SHM system's actuator and receiver. Environmental and operational conditions can affect structure properties and measured acceleration signals, making it challenging to infer the real condition of the structure. To address this, we propose a drive-by damage detection method using a classification model with a Convolutional Neural Network (CNN). CNNs understand connectivity patterns between neurons, inspired by the animal visual cortex. The 1D CNN identifies damage from raw acceleration signals at the front boogie of a train. Training data generated by a finite element method considers healthy and damaged bridge conditions. The paper focuses on identifying scour-induced damage, resulting from the loss of stiffness in the bridge support due to erosion. Extensive numerical experiments evaluate the effectiveness and robustness of the 1D CNN approach.

Keywords: Convolutional Neural Network, Railway bridges, Structural Health Monitoring, Machine Learning, Data Analysis

1 Introduction

The aging and deterioration of civil engineering infrastructure poses significant challenges to ensuring public safety and efficient transportation. Structural Health Monitoring (SHM) has emerged as a critical tool in assessing the structural integrity and data-driven models have shown promise in this field. However, widespread bridge instrumentation across an entire network is often logistically difficult and expensive, prompting the development of alternative approaches, such as the drive-by or indirect monitoring method look promising considering the low demand for human labor. In the drive-by approach, the model was based on the studies of Fitzgerald et al. [1], OBrien et al. [2] and Fernandes [3], where the instrumented vehicle serves as both the actuator and receiver of the SHM system, making it an attractive solution for large-scale monitoring. However, this method introduces complexities due to environmental factors (e.g., temperature) and varying operational conditions (e.g., changing velocity), which can impact the measured acceleration signals and obscure the true condition of the structure. To address these challenges, this paper proposes an innovative drive-by damage detection methodology based on a classification model utilizing Convolutional Neural Networks (CNN's). CNN's are a class of feed-forward artificial neural networks that have been inspired by the organization of the animal visual cortex, making them powerful tools for image recognition tasks. In this context, a specialized 1D CNN is employed to identify damage from raw acceleration signals obtained at the front boogie of a train during its passage over the bridge. The classification strategy utilized for damage detection involves training the 1D CNN with data generated using a finite element method, considering the healthy (Baseline data) and damaged conditions of the bridge, which will be made analysis with 5, 10, 20 and 50 percent damage. The focus of this study is to identify damage caused by scour, witch is a a phenomenon characterized by the loss of stiffness in the bridge support due to erosion. To demonstrate the effectiveness and robustness of the proposed 1D CNN approach, extensive numerical experiments are conducted. These experiments evaluate the model's ability to accurately identify and classify damage under various environmental and operational scenarios, providing valuable insights for real-world application.

2 Proposed Framework

Given the continuous aging of structures and the increasing traffic each year, bridges are becoming progressively more hazardous to use. As said by Fernandes [3], this underscores the importance of investing in structural health monitoring, which can aid in averting potential collapses, ensuring the safety of both individuals and the bridge itself. This paper aims to identify scour damage through a data-driven method that involves simulation data.

The structural health monitoring (SHM) method can be divided into two main sections. The first section deals with data generation, where bridge data is produced under baseline conditions or with various levels of simulated damage using mathematical methods. The second section involves the model, which remains completely independent of the physical structure. This model serves to identify patterns for classification, considering distinct scenarios of damage. In this case, a one-dimensional convolutional neural network is employed.

2.1 Data Acquisition

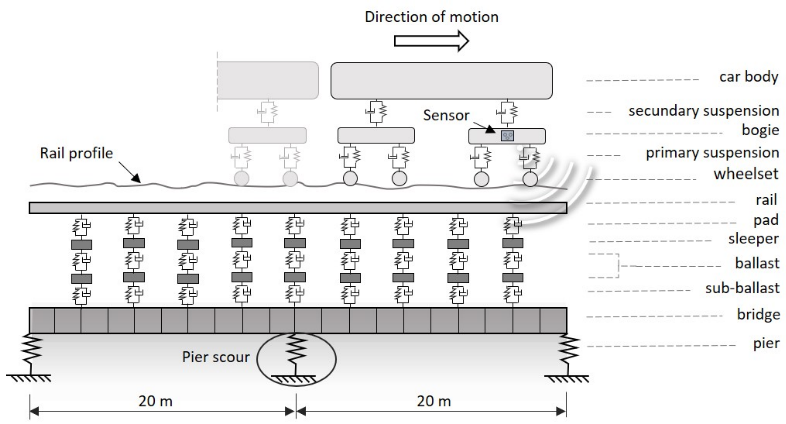

Figure 1. Numerical model for the data acquisition

The process of data acquisition relies on numerical simulations. As illustrated in Figure 1, this method involves simulating the passage of a train consisting of five vehicles across a bridge. Throughout the simulation, various operational variables are taken into account, including train speed, rail irregularities, and measurement noise. The scour witch will be identified in the data is characterized by soil erosion around the foundation, resulting in the degradation of reinforced concrete, corrosion in steel components, and impairment of other structural supports. Following this guideline, vertical acceleration values are specifically collected at the frontal boogie of the train, a location sensitive to scour damage, which is indicated at the pier in Figure 1. These vertical acceleration values are generated at different time intervals during the train's journey across the bridge. This accumulation of data points provides a comprehensive dataset for subsequent processes related to the detection of structural damage. To ensure a comprehensive grasp of vibrations, data collection spans the entire duration of the train's presence on the bridge, taking into account the bridge's length of 4000 meters and the train's length of 1830 meters.

2.2 Damage Detection

As mentioned in the introduction, the data was divided into five categories: baseline, 5, 10, 20, and 50 percent damage. Each category represents a different level of damage to the bridge. To visualize these variations, plots were created for each category, as shown in Figure 2. The visual analysis of the plots allows for easy identification of the differences between the baseline and the 50 damage cases, which are noticeably distinguishable by the human eye. Conversely, the difference between the 5 percent damage and the baseline is nearly imperceptible. With these plots, we gain insights into the impact of damage on the bridge's vibration patterns, which will be

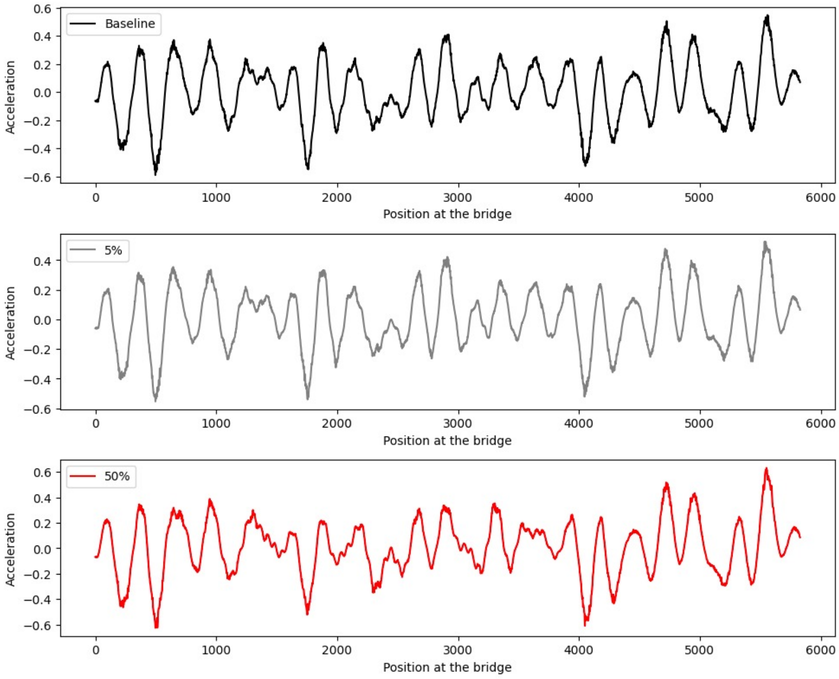

Figure 2. Data of the bridge considering 5830 meters.

essential for subsequent analysis and model development. To categorize simulations effectively, we used a type of artificial intelligence called a 1D Convolutional Neural Network (CNN). This choice was based on its ability to work efficiently and produce accurate results. In fact, compared to other methods we tried, such as Search Trees and unsupervised methods, the 1D CNN achieved about 20 percent higher accuracy.

2.3 How a CNN Works

The 1D CNN works in three main steps, which are like building blocks:

Convolutional Layer: This step helps the network understand the important patterns in the data. It looks at different parts of the input data and learns what is significant in each area. For our case, it focuses on the vibrations along the bridge.

Pooling Layer: After the first step, we need to simplify the information while keeping the important parts. The pooling layer does this by reducing the complexity of the data without losing its critical features. It helps make the process faster and prevents the model from making mistakes due to too much detail.

Flatten Layer: The flatten layer helps connect the earlier convolutional and pooling layers to the next dense (fully connected) layers. It changes the multi-picture shapes from the convolutional layers into a flat line that works well with the dense layers.

Dense Layer (Fully Connected Layer): This final step looks at all the information gathered so far and tries to understand complex patterns. It brings everything together to make the final decision about the bridge's condition.

By combining these four steps, the 1D CNN becomes very good at recognizing intricate patterns and con-

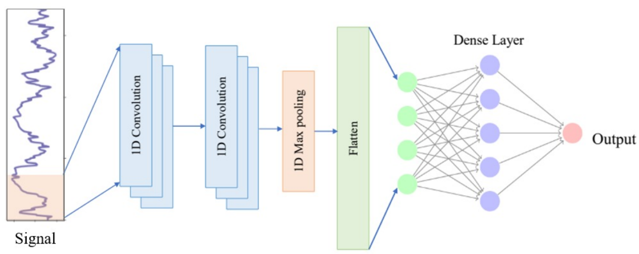

Figure 3. The convolutional neural network (CNN) model architecture for sensor data from Vadamalraj et al. [4]

nections in the vibration data. This makes it a powerful tool for our goal of identifying variations in the bridge's condition. We can see a visual representation in Figure 3.

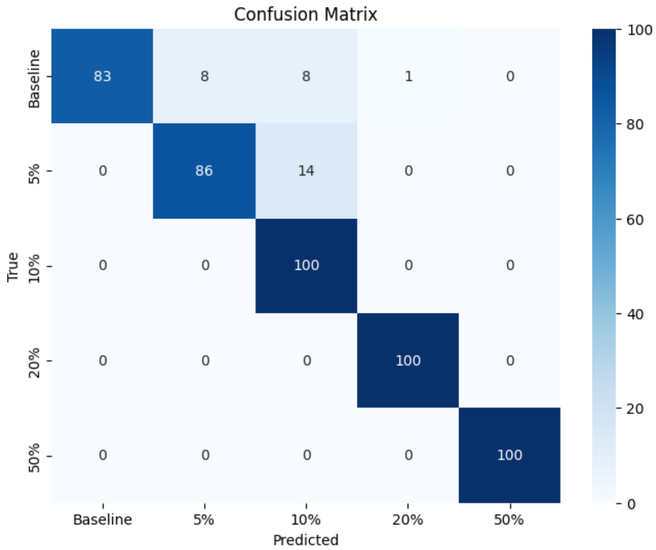

Figure 4. Performance of the Model

As shown in Figure 4, a Confusion Matrix was used to evaluate the model's precision by predicting 100 test data for each scenario. The output layer of the model consists of five units, each corresponding to a specific damage label. Analyzing the results, it's apparent that the model faces challenges in identifying cases with low or no damage. Despite this limitation, the model demonstrates a notably high precision, making it promising for damage detection scenarios.

To further assess the model's precision, two additional models were created, focusing solely on the baseline, 5 percent damage, and baseline 10 percent damage scenarios. These models aimed to test the model's efficacy in identifying subtle or minimal damage situations. The model trained on the baseline and 5 percent damage achieved an average precision of 90 percent, while the model involving baseline and 10 percent damage reached a precision of 95 percent. These outcomes underscore the model's strong performance in scenarios with low damage levels.

The Confusion Matrix, combined with precision assessments, offers valuable insights into the model's strengths and limitations. It guides our understanding of how effectively the model can handle various damage scenarios. Additionally, we constructed another plot that presents predictions for each scenario individually. The x-axis indicates the predicted damage scenario, while the y-axis illustrates the outcomes when predicting scenarios where the bridge is in a healthy state. As the bridge's damage level gradually increases, the plot demonstrates that the model's accuracy in identifying damage improves, particularly when the damage exceeds 10 percent. However, some errors are observed in scenarios with 10, 5, and baseline damage cases.

The model's predictions for different damage scenarios can serve as an illustrative example of how it would perform over 100 passages across the bridge, gradually accumulating structural damage. This insight offers a valuable perspective on its practical functionality in real-life scenarios, shedding light on its potential operational behavior with a pretty good precision.

3 Conclusions

In conclusion, the research demonstrates that 1D Convolutional Neural Networks excel in effectively handling sensor-captured data and accurately classifying it into distinct groups. Leveraging its ability to identify patterns efficiently with low computational cost, the 1D CNN proves to be a powerful tool for Drive-by damage detection with the scour induced method. The results suggest that using CNNs is a highly promising approach for Structural Health Monitoring (SHM), offering great potential for future applications in similar scenarios. The success of the CNN model underscores the significance of leveraging artificial intelligence techniques for efficient and accurate damage detection in structural analysis.

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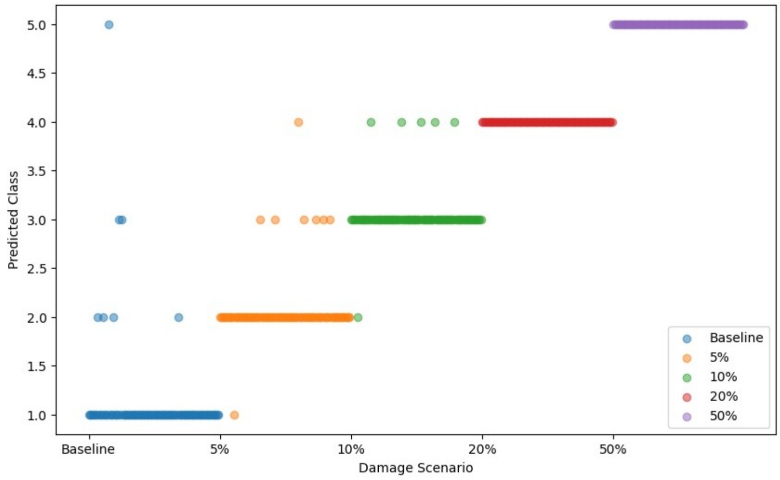

Figure 5. Model Predictions for Different Damage Scenarios

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