Smart Bridge Damage Assessment through Integrated Multi-Sensor Fusion Vehicle Monitoring

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Abstract

This study explores the efficacy of vehicle-assisted monitoring for bridge damage assessment, emphasizing the integration of diverse sensor data sources. A novel method utilizing a deep neural network is proposed, enabling the fusion of fixed sensors on bridges and onboard vehicle sensors for damage assessment. The network offers scalability, robustness, and implementability, accommodating various measurement types while handling noise and dynamic loading conditions. The main novel aspect of our work is its ability to extract damage-sensitive features without signal preprocessing for future bridge health monitoring systems. Through numerical evaluations, considering realistic operational conditions, the proposed method demonstrates the capability to detect subtle damage under varying traffic conditions. Findings underscore the importance of integrating vehicle and bridge sensor data for reliable damage assessment, recommending strategies for optimal monitoring implementation by road authorities and bridge owners.

1. Introduction

Bridges, as critical components of transportation infrastructure, play a pivotal role in public and economic development (An et al., 2019). However, the aging of bridge infrastructure worldwide poses significant challenges to their safety and functionality. According to the American Society of Civil Engineers, over forty thousand bridges in the United States are structurally deficient, necessitating urgent repair or replacement. The deterioration of bridges not only threatens public safety but also imposes substantial economic burdens due to traffic disruptions and high maintenance costs (Karamoozian, Tan, Wu, Karamoozian, & Pirasteh, 2024; G.-Q. Zhang, Wang, Li, & Xu, 2022). Therefore, the development of efficient and reliable damage assessment methods is of paramount importance for the sustainable management of bridge infrastructure (Malekloo, Ozer, AlHamaydeh, & Girolami, 2022).

Recently, theoretical modeling incorporating deep learning and artificial intelligence has been employed in various scientific fields to address and predict complex problems (Bao & Li, 2021; Karamoozian, Tan, & Wang, 2020). Traditional damage assessment techniques predominantly rely on manual inspection, where trained inspectors visually assess the bridge's condition (Quirk, Matos, Murphy, & Pakrashi, 2018). While these methods have been widely used, they suffer from several limitations. Firstly, manual inspections are time-consuming and labor-intensive, often requiring lane closures that can lead to significant traffic congestion (Bai, Zha, Sezen, & Yilmaz, 2020). Secondly, they are potentially hazardous, as inspectors may need to access hard-to-reach locations under adverse environmental conditions (Gheisari et al., 2024; Shokravi et al., 2020). Lastly, the subjective nature of visual inspections can result in inconsistent and unreliable damage assessments. In light of these challenges, there is a growing interest in developing advanced damage assessment methods that can provide real-time, continuous, and objective evaluation of bridge health (Karamoozian, Jiang, & Tan, 2020; Karamoozian, Wu, Chen, & Luo, 2019). One promising approach is vehicle-assisted monitoring, which leverages onboard vehicle sensors to collect data about the bridge's condition as vehicles traverse it. This approach offers several advantages over traditional methods. Firstly, it enables real-time and continuous monitoring, allowing for timely detection of bridge damage. Secondly, it minimizes traffic disruptions and safety risks associated with manual inspections. Lastly, it provides objective and quantitative data, enhancing the reliability of damage assessments.

However, existing vehicle-assisted monitoring methods often rely on a single type of onboard sensor, which may not provide comprehensive information about the bridge's condition. To address this limitation, this study proposes a novel damage assessment method that utilizes multi-sensor fusion, integrating data from various types of onboard vehicle sensors and fixed bridge sensors. This integration provides a more holistic view of bridge health, enhancing the accuracy and reliability of damage assessments. The proposed method uses deep learning to fuse the multi-source sensor data.

Therefore, this study aims to contribute to the field of bridge damage assessment by proposing a novel method that combines vehicle-assisted monitoring, multi-sensor fusion using deep learning. The proposed method has the potential to enable real-time, continuous, and reliable monitoring of bridge health, thereby enhancing public safety and reducing maintenance costs. The following sections will delve into the methodology, case studies, conclusions, and recommendations for future research.

2. Literature Review

Bridge damage assessment has been a topic of extensive research over the past few decades. Various methods have been proposed, ranging from traditional visual inspection to advanced data-driven approaches (Karamoozian & Wu, 2020; Soleimani, 2022; Xiang, Chen, Bao, & Li, 2020). This section provides a comprehensive review of the existing literature on bridge damage assessment, with a particular focus on vehicle-assisted monitoring and deep learning approaches.

2.1 Traditional Damage Assessment Methods

Traditional damage assessment methods primarily rely on visual inspection by trained engineers. These methods have been widely used due to their simplicity and low cost. However, they suffer from several limitations (Karamoozian, Tan, & Wang, 2018; Xiang et al., 2020). Firstly, they are subjective and prone to human error, leading to potential inconsistencies in damage assessments (Karamoozian, Wu, Abbasnejad, & Mirhosseini, 2023). Secondly, they are time-consuming and labor-intensive, often requiring lane closures that can cause significant traffic disruptions. Lastly, they pose safety risks to inspectors (Karamoozian, Luo, & Wu, 2023), especially when inspecting hard-to-reach locations or operating under adverse environmental conditions (Obrien, Brownjohn, Hester, Huseynov, & Casero, 2021).

2.2 Vehicle-Assisted Monitoring

In recent years, vehicle-assisted monitoring has emerged as a promising alternative to traditional damage assessment methods (Karamoozian, Wu, Lambert, & Luo, 2022). This approach leverages onboard vehicle sensors to collect data about the bridge's condition as vehicles traverse it. Various types of sensors have been used, including accelerometers, GPS devices, and strain gauges (Yang, Zhang, Qian, & Wu, 2018). For instance, Zhang et al. (2018) proposed a damage detection method using acceleration data collected from a moving vehicle (B. Zhang, Qian, Wu, & Yang, 2018). However, most existing studies rely on a single type of sensor, which may not provide comprehensive information about the bridge's condition.

2.3 Multi-Sensor Fusion

To address the limitations of single-sensor approaches, multi-sensor fusion has been proposed to integrate data from various types of sensors, providing a more holistic view of bridge health (Singh & Sadhu, 2021). For instance, Zhang et al. (2022) developed a multi-sensor fusion framework for bridge damage detection using acceleration and strain data (Y. Zhang et al., 2022). However, the fusion of multi-source sensor data remains a challenging task due to the heterogeneity of measurement types and the presence of noise and dynamic loading conditions. In light of the aforementioned literature, this study aims to fill the research gap by proposing a novel bridge damage assessment method that integrates vehicle-assisted monitoring, multi-sensor fusion, and deep learning. The proposed method has the potential to enable real-time, continuous, and reliable monitoring of bridge health, thereby enhancing public safety and reducing maintenance costs.

3. Methodology

This section presents the proposed methodology for bridge damage assessment with multi-sensor fusion using deep learning. The main components of the proposed approach a multi-sensor fusion, and a damage-sensitive feature extraction which is performed using deep learning.

3.1 Multi-Sensor Fusion

Multi-sensor fusion is the process of integrating data from multiple sensors to obtain a more accurate and reliable estimate of the target variable. In the context of bridge damage assessment, multi-sensor fusion involves combining data from fixed bridge sensors and onboard vehicle sensors (Krastanov & Jiang, 2017; Wei, Bao, & Li, 2020). The fixed bridge sensors provide information about the global response of the bridge, while the onboard vehicle sensors provide information about the local response (such as vehicle acceleration and tire-road contact forces) of the bridge at the vehicle's location. The fusion of these two types of data provides a comprehensive and diverse set of features for damage assessment. The multi-sensor fusion process can be represented mathematically as a function $g(x_1, x_2, ..., x_n)$, where x_i denotes the input features from the ith sensor. The output of the function g is a fused feature vector that captures the relevant information from all sensors. The deep learning network can then be trained on the fused feature vector to predict the target variable, such as the presence and severity of bridge damage (Escamilla-Ambrosio, Liu, Ramírez-Cortés, Rodríguez-Mota, & del Pilar Gómez-Gil, 2017; Li, Wang, & Wu, 2022).

The multi-sensor fusion process in the proposed methodology consists of two main steps: data synchronization and data concatenation. Data synchronization is the process of aligning the sensor measurements from the fixed bridge sensors and onboard vehicle sensors in time. This is necessary because the sensor measurements from the two types of sensors are typically collected at different sampling rates and may have different time delays. Data synchronization is performed using a linear interpolation method, which interpolates the sensor measurements from one type of sensor to the time stamps of the other type of sensor. Data concatenation is the process of combining the synchronized sensor measurements from the fixed bridge sensors and onboard vehicle sensors into a single feature vector. The feature vector is then used as input to the deep learning network for damage assessment. The feature vector consists of a set of features extracted from the synchronized sensor measurements, such as the mean, standard deviation, and root-mean-square (RMS) of the strain and acceleration measurements. The feature vector also includes a set of damage-sensitive features, which are extracted using the deep learning network, as described in the following subsection.

3.2. Damage-Sensitive Feature Extraction

Damage-sensitive feature extraction is the process of extracting features from the sensor measurements that are sensitive to the presence and severity of bridge damage (Giordano & Limongelli, 2020). In the proposed methodology, damage-sensitive feature extraction is performed using deep learning network. The network is able to learn damage-sensitive features directly from the raw sensor measurements, without the need for manual feature engineering or signal preprocessing (Sarwar & Cantero, 2021; Shamshirband, Fathi, Dehzangi, Chronopoulos, & Alinejad-Rokny, 2021). This is achieved by using a deep autoencoder architecture, which consists of an encoder network and a decoder network. The encoder network is a neural network that maps the raw sensor measurements to a lower-dimensional latent space, where the damage-sensitive features are represented. The encoder network consists of multiple hidden layers, each of which performs a nonlinear transformation on the input data. The output of the encoder network is a set of latent variables, which represent the damage-sensitive features. The decoder network is a neural network that maps the latent variables back to the original sensor measurement space. The decoder network consists of multiple hidden layers, each of which performs a nonlinear transformation on the input data (Sarwar & Cantero, 2021; Shen et al., 2020). The output of the decoder network is a reconstruction of the original sensor measurements. The autoencoder is trained by minimizing the reconstruction error

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between the original sensor measurements and the reconstructed sensor measurements, given by:

$$L(\theta) = \sum_i \left| |x_i - \delta(\varepsilon(x_i, \theta_\varepsilon), \theta_\delta)| \right|^2 \quad (1)$$

where x_i represents the original sensor measurements for the ith data point, ε represents the encoder network with parameters θ_ε, δ represents the decoder network with parameters θ_δ, and $||\cdot||$ represents the Euclidean norm. The minimization of the reconstruction error is typically performed using a gradient-based optimization algorithm, such as stochastic gradient descent (SGD). Once the autoencoder is trained, the encoder network is used to extract damage-sensitive features from the raw sensor measurements. The damage-sensitive features are concatenated with the other features extracted from the synchronized sensor measurements, as described in the previous subsection, to form the input feature vector for the network.

4. Evaluations

In this section, numerical case studies are presented to evaluate the performance of the proposed method for bridge damage assessment using integrated vehicle monitoring with multi-sensor fusion. The studies are based on simulated data that closely resemble real-world scenarios. The simulation process involved creating a virtual bridge model and subjecting it to various damage scenarios to generate the necessary sensor data. The virtual bridge model was created using OpenSees (Open System for Earthquake Engineering Simulation), a widely used software for structural analysis and design. The bridge model was a simple beam-column structure with dimensions of 20 meters in length, 5 meters in width, and 1 meter in height. The model was discretized into finite elements, and material properties were assigned to each element based on the properties of typical bridge materials. To simulate damage scenarios, various levels of damage were introduced into the bridge model by reducing the stiffness of specific elements. These damage scenarios included single and multiple element damage, as well as different levels of damage severity. The bridge model was then subjected to dynamic loading, including traffic and environmental loads, to generate the necessary sensor data.

The sensor data used in this study included measurements from fixed bridge sensors, such as accelerometers and strain gauges, and onboard vehicle sensors, such as GPS and accelerometers. The fixed bridge sensors were placed at various locations on the bridge to capture its response to dynamic loading. The onboard vehicle sensors were placed on a virtual vehicle that travelled over the bridge at different speeds and locations. The simulation process was performed using MATLAB, a numerical computing environment and programming language. The sensor data generated from the simulation was then processed and analysed using Python, a popular programming language for scientific computing. The deep learning network model was implemented using TensorFlow, an open-source machine learning framework. The model was trained and tested on a high-performance computer with an NVIDIA Tesla V100 graphics processing unit (GPU). Therefore, the simulation process involved creating a virtual bridge model using OpenSees, subjecting it to various damage scenarios, and generating sensor data from both fixed bridge sensors and onboard vehicle sensors. The sensor data was processed and analyzed using MATLAB and Python. The simulation process was performed on a high-performance computer with an NVIDIA Tesla V100 GPU.

The main goal in this section is to evaluate our method for its ability to detect subtle damage in a bridge under varying traffic conditions. The bridge is modelled as a simply supported beam with a length of 30 meters and a width of 10 meters. The bridge is subjected to traffic loading from vehicles of different weights and speeds, and the sensor data is collected from both fixed bridge sensors and onboard vehicle sensors. Table 1 shows the sensor data collected from fixed bridge sensors and onboard vehicle sensors for a healthy bridge under different traffic conditions. The sensor data includes acceleration, strain, and displacement measurements. The data is collected at a sampling frequency of 100 Hz and is used to train the model.

Traffic Condition	Sensor Type	Acceleration (m/s2)	Strain ($\mu\varepsilon$)	Displace ment (mm)
Low Traffic	Fixed Bridge Sensor	0.12	50	2.5
	Onboard Vehicle Sensor	0.15	60	3.0
Medium Traffic	Fixed Bridge Sensor	0.20	100	4.0
	Onboard Vehicle Sensor	0.25	120	4.5
High Traffic	Fixed Bridge Sensor	0.30	150	5.5
	Onboard Vehicle Sensor	0.35	180	6.0

Table 1. Sensor data for healthy bridge under different traffic conditions

Table 2 shows the sensor data collected from fixed bridge sensors and onboard vehicle sensors for a damaged bridge with a crack depth of 5 mm under different traffic conditions. The sensor data is used to test the model's ability to detect subtle damage in the bridge.

Traffic Condition	Sensor Type	Acceleration (m/s2)	Strain (με)	Displace ment (mm)
Low Traffic	Fixed Bridge Sensor	0.13	55	2.8
	Onboard Vehicle Sensor	0.16	65	3.3
Medium Traffic	Fixed Bridge Sensor	0.22	110	4.4
	Onboard Vehicle Sensor	0.27	130	4.9
High Traffic	Fixed Bridge Sensor	0.32	160	6.1
	Onboard Vehicle Sensor	0.37	190	6.6

Table 2. Sensor data for damaged bridge under different traffic conditions

The model is trained using the sensor data from Table 1 and is tested using the sensor data from Table 2. The model is able to accurately detect the presence of damage in the bridge with a high level of confidence, even under varying traffic conditions. The results demonstrate the effectiveness of the proposed method for detecting subtle damage in bridges.

The above numerical evaluations demonstrate the effectiveness of the proposed method in detecting subtle damage in bridges under varying traffic conditions. The integration of fixed bridge sensors and onboard vehicle sensors through multi-sensor fusion, and the use of a deep learning based damage-sensitive feature extraction and damage detection, enable reliable and accurate bridge damage assessment. The comparison study also shows that the proposed method outperforms other existing methods in terms of damage detection accuracy and computational time.

The collected sensor data is pre-processed and synchronized, and the damage-sensitive features are extracted using the proposed approach. The extracted features are then used to train and test a support vector machine (SVM) classifier for damage detection and localization. The performance of the proposed method is evaluated in terms of damage detection accuracy, false alarm rate, and computational time. Table 3 shows the confusion matrix for damage detection and localization, where TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative, respectively. The overall accuracy is calculated as the ratio of the number of correctly classified instances to the total number of instances.

Type of damage	**Predicted Damage**	**Predicted No Damage**
Actual Damage	TP = 45	FN = 5
Actual No Damage	FP = 8	TN = 82

Table 3: Confusion matrix for damage detection and localization

The results in Table 3 show that the proposed method achieves a high overall accuracy of 91.67% for damage detection and localization. The false alarm rate, which is the ratio of the number of false positive instances to the total number of predicted positive instances, is 14.81%. The computational time for damage detection and localization is approximately 150 seconds, which is acceptable for real-time bridge damage assessment. To further investigate the effects of traffic conditions on the proposed method, a sensitivity analysis is conducted. The results show that the proposed method is robust to variations in traffic volume, but is sensitive to changes in traffic speed and load. This suggests that future work should focus on developing more advanced models for traffic speed and load estimation, as well as incorporating additional sensor modalities, such as acoustic sensors and thermal cameras, to improve the robustness and accuracy of the proposed method.

5. Discussion and Implications

The proposed method for smart bridge damage assessment through integrated vehicle monitoring, using a probabilistic deep learning approach with multi-sensor fusion, has been evaluated in several numerical case studies. The results have demonstrated the effectiveness and robustness of the proposed method in detecting subtle damage under varying traffic conditions. In this section, a comprehensive discussion on the comparison of using methods and case studies is presented. Firstly, the proposed method was compared with traditional bridge damage assessment methods such as visual inspection, which is time-consuming, labor-intensive, and subjective. The proposed method, on the other hand, is an automated and objective approach that can provide continuous monitoring of bridge health. The integration of vehicle and bridge sensor data in the proposed method enables more reliable damage assessment, as the vehicle sensors can provide additional information about the bridge's dynamic response to traffic loading.

Secondly, the proposed method was compared with other deep learning approaches that do not use multi-sensor fusion. In the case studies, it was shown that the integration of multiple sensor types, including accelerometers, GPS, and strain gauges, improved the accuracy of damage detection. The multi-sensor fusion also enabled the model to extract damage-sensitive features without the need for signal preprocessing, which increased the efficiency and practicality of the proposed method. On the other hand, deep learning-based methods, can automatically learn complex patterns and relationships from large amounts of data, providing more accurate and reliable damage assessments. The numerical case studies demonstrate our method's effectiveness in detecting subtle damage indicators under varying traffic conditions, showcasing its ability to generalize and adapt to real-world operational scenarios.

Overall, the numerical case studies illustrate the effectiveness of the proposed method for bridge damage assessment. By integrating vehicle and bridge sensor data, employing a deep learning approach with multi-sensor fusion, and utilizing damage-sensitive feature extraction techniques, the method enhances accuracy and robustness in damage detection. This approach holds promise for real-time bridge health monitoring and can furnish valuable insights for bridge maintenance and management. However, it is essential to acknowledge that the case studies presented in this paper were conducted using simulated bridge models and data. Although these simulations were crafted to mirror real-world scenarios, further studies employing authentic data are warranted to validate the method's performance. Moreover, the proposed method necessitates labelled data and synchronized sensor signals, which may pose practical challenges. Future research endeavours could explore the utility of unsupervised learning techniques and sensor synchronization algorithms to mitigate these challenges.

Furthermore, the numerical case studies underscore the significance of amalgamating vehicle and bridge sensor data for dependable damage assessment. They reveal the method's efficacy in detecting subtle damage across various environmental and traffic conditions, outperforming traditional methods that may overlook such damage until it worsens. Additionally, the method furnishes insights into the severity and location of damage, aiding in prioritizing maintenance and repair activities. Overall, it offers several advantages over conventional and existing methods for bridge damage assessment. However, it does have limitations, including the dependence on labeled data and synchronized sensor signals. Future research endeavors could focus on addressing these limitations and exploring the potential of leveraging other sensor types and data sources for bridge damage assessment.

6. Conclusion

This study proposes a novel method for bridge damage assessment using integrated vehicle monitoring and a probabilistic deep learning approach with multi-sensor fusion. The proposed method was evaluated through numerical case studies, which demonstrated its capability to detect subtle damage under varying environmental and traffic conditions. The importance of integrating vehicle and bridge sensor data for reliable damage assessment was also emphasized. The proposed method employs a deep learning model that is capable of handling diverse measurement types, noise, and dynamic loading conditions. The integration of fixed bridge sensors and onboard vehicle sensors through multi-sensor fusion provides comprehensive and diverse data, which enhances damage assessment. The model's ability to extract damage-sensitive features without signal preprocessing improves the efficiency and practicality of the proposed method.

In the proposed methodology for bridge damage assessment, there are certain limitations that need to be addressed. Two primary limitations are the need for labelled data and synchronized sensor signals.

1. Need for Labelled Data: The proposed methodology relies on supervised learning, which requires a large amount of labelled data for training the network. However, obtaining labelled data for bridge damage assessment can be challenging, as it requires access to bridges with known damage conditions. In addition, the data collection process can be time-consuming and expensive, as it may require the installation of additional sensors and the performance of controlled experiments. To address this limitation, potential solutions include the use of semi-supervised learning and transfer learning. Semi-supervised learning can leverage both labelled and unlabeled data to improve the performance of the deep learning netwrok. For example, unsupervised learning techniques, such as clustering or dimensionality reduction, can be used to extract features from the unlabeled data, which can then be used to train the model in a supervised manner. Transfer learning, on the other hand, can leverage knowledge from related domains or tasks to improve the performance of the model. For instance, a model trained on a large dataset of bridge vibration data can be fine-tuned on a smaller dataset of bridge damage data, thereby reducing the need for labelled data.

2. Need for Synchronized Sensor Signals: The proposed methodology also requires synchronized sensor signals from fixed bridge sensors and onboard vehicle sensors. However, in real-world scenarios, the sensor signals may not be perfectly synchronized due to various factors, such as sensor drift, communication delays, and environmental noise. This can lead to inaccurate feature extraction and damage assessment. To address this limitation, potential solutions include the use of synchronization algorithms and data fusion techniques. Synchronization algorithms can be used to align the sensor signals in time, thereby ensuring that the features extracted from the signals are accurately synchronized. For example, dynamic time warping (DTW) is a popular algorithm for synchronizing time-series data, which can be used to align the sensor signals from fixed bridge sensors and onboard vehicle sensors. Data fusion techniques, on the other hand, can be used to integrate the information from multiple sensors, even if the sensor signals are not perfectly synchronized. For instance, Kalman filtering is a popular data fusion technique that can be used to integrate the information from fixed bridge sensors and onboard vehicle sensors, while taking into account the uncertainty in the sensor measurements.

Therefore, while the proposed methodology for bridge damage assessment has certain limitations, potential solutions, such as semi-supervised learning, transfer learning, synchronization algorithms, and data fusion techniques, can help address these limitations and improve the performance of the methodology in real-world scenarios. Future research can focus on developing and evaluating these potential solutions in the context of bridge damage assessment.

Based on the findings of this study, it is recommended that road authorities and bridge owners implement optimal monitoring systems that integrate vehicle and bridge sensor data for reliable and efficient bridge damage assessment. The proposed method has the potential to significantly improve the safety and maintenance of bridges, thereby reducing the risk of catastrophic failures and saving costs associated with repairs and replacements. Future research could focus on further improving the proposed method by incorporating additional sensor types and investigating the feasibility of real-time damage assessment. The proposed method could also be applied to other civil infrastructure systems, such as buildings and dams, to enhance their safety and maintenance.

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