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Unsupervised Machine Learning Application for Structural Health Monitoring

Massimo Maffeis and Filippo Gerin*

Maffeis Engineering SpA, Solagna(VI), Italy

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***Corresponding author:** Filippo Gerin, Maffeis Engineering SpA, Solagna(VI), Italy

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Abstract

This research delves into a transformative approach to bridge health monitoring, introducing unsupervised machine learning, with a specific emphasis on acoustic characteristics. The aim is to revolutionize traditional physics-based methods, motivated by the constraints inherent in conventional structural health monitoring heavily reliant on manual inspections. Leveraging techniques such as Mel-frequency cepstral coefficients (MFCC), we transform acoustic features to serve as the foundation for a neural network's classification capabilities. This innovative methodology enables the discernment between healthy and potentially compromised bridge conditions.

Keywords: Structural health monitoring; Unsupervised machine learning; Feature extraction; Classification; Autoencoder; Mel-frequency cepstral coefficients; ADA Bridge; Self-Supervised learning

Abbreviations: MFCC: Mel-frequency Cepstral Coefficients; NN: Neural Network; PCA: Principal Component Analysi

Introduction

Bridges serve as critical components of our infrastructure, facilitating the smooth flow of transportation and connectivity. Ensuring the structural integrity and health of these vital assets is paramount to public safety and the longevity of civil engineering investments. In this context, our study seeks to revolutionize traditional methods of bridge health monitoring by harnessing the power of unsupervised machine learning, specifically focusing on acoustic characteristics as a novel indicator. The motivation behind this research stems from the limitations of conventional structural health monitoring systems, which often rely on manual inspections and predefined threshold-based alarms. These methods may fall short in detecting subtle structural changes or anomalies that could lead to potential safety hazards. By leveraging advancements in machine learning, particularly in speaker recognition techniques, we aim to capture and interpret the intricate acoustic patterns emitted by bridges during their operational lifespan. Our approach involves treating acceleration time series as analogous to voice recordings, opening new possibilities for comprehensive bridge health assessment. The utilization of feature extraction methods, such as frequency-based features and Mel-frequency cepstral coefficients (MFCC), allows us to transform raw data into meaningful representations that capture the nuances of bridge soundscapes. These transformed features serve as the foundation for our subsequent classification efforts, where a neural network plays a pivotal role in discerning healthy and potentially compromised bridge conditions.

Discussion

MFCC features in bridge health monitoring

We've reframed our challenge by utilizing MFCC, the industry-standard features in speaker recognition, effectively casting our bridge health monitoring into the realm of speaker identification. Our objective is to decipher whether the bridge undergoes alterations in its "voice" over time, serving as a potential indicator of structural health changes. This innovative approach allows us to investigate whether the acoustic characteristics of the bridge today align with those from the past, essentially gauging the consistency of the bridge's "speech" across its lifespan. The application of MFCC features introduces a groundbreaking shift in our monitoring methodology, showcasing remarkable stability and resilience compared to raw frequencies. By integrating MFCC with environmental measures, we establish a linkage between changes in MFCC and shifts in environmental conditions. This fusion enables us to compare the bridge's health across extreme load scenarios or environmental accidents, providing a comprehensive understanding of its condition under varied circumstances. This comparative analysis serves as a powerful tool for tracking the bridge's health dynamics across diverse conditions.

Dynamic classification with a neural network

The infusion of the neural network introduces dynamism into the classification process, adeptly condensing the feature space to identify specific regions indicative of healthy bridge recordings, where traditional static handcrafted techniques fall short. Beyond mere compression, the neural network transforms into a discerning classifier, establishing a threshold that capitalizes on its understanding of the dataset's distribution under healthy conditions. The inherent strength of the neural network lies in its adaptability to encountered data. Crucially, its adaptive nature eliminates the need for manual checks in every instance, showcasing an exceptional ability to seamlessly tailor itself to each case and condition. Moreover, the monitoring unfolds in real-time, triggering a swift alarm at the occurrence of any damage.

Test case: ADA Bridge

In this section, we show the results on acceleration response data from the Old ADA bridge in Japan [1], conducting an experiment with artificial damage. Vehicle access was restricted to the test vehicle and ambient and vehicle-induced vibration data were collected. The vertical truss T1 at the bridge midspan underwent sequential actions: halving (DC1), full cutting (DC2), repair (DC3), and complete cutting of vertical truss T2 (DC4). Figure 1 illustrates the distributions of the first two principal components derived from MFCC features of sensor A3. Training used vehicle data from the DC3 repaired condition, and testing involved the DC4 damage condition [2,3].

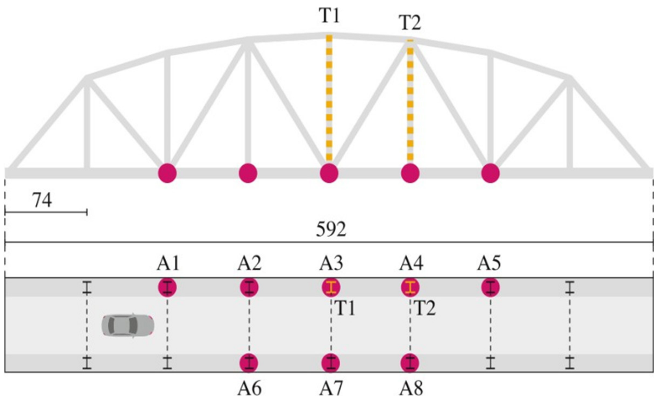

Figure 1: Schematic representation of the ADA bridge, along with sensors placement (A1-A8) and damaged sections (T1-T2).

In Figure 2, we illustrate the distributions resulting from PCA analysis performed on MFCC extracted from the data, specifically focusing on the results obtained using MFCC features from sensor A3. During the training phase, vehicle data from the DC3 repaired condition was utilized, while testing involved the DC4 damage condition. The healthy state of ADA Bridge is represented by green dots, while test data is color-coded in blue for healthy and red for damaged conditions. It's worth highlighting that any deviation of the test data from the typical healthy range results in a classification of damage [4,5].

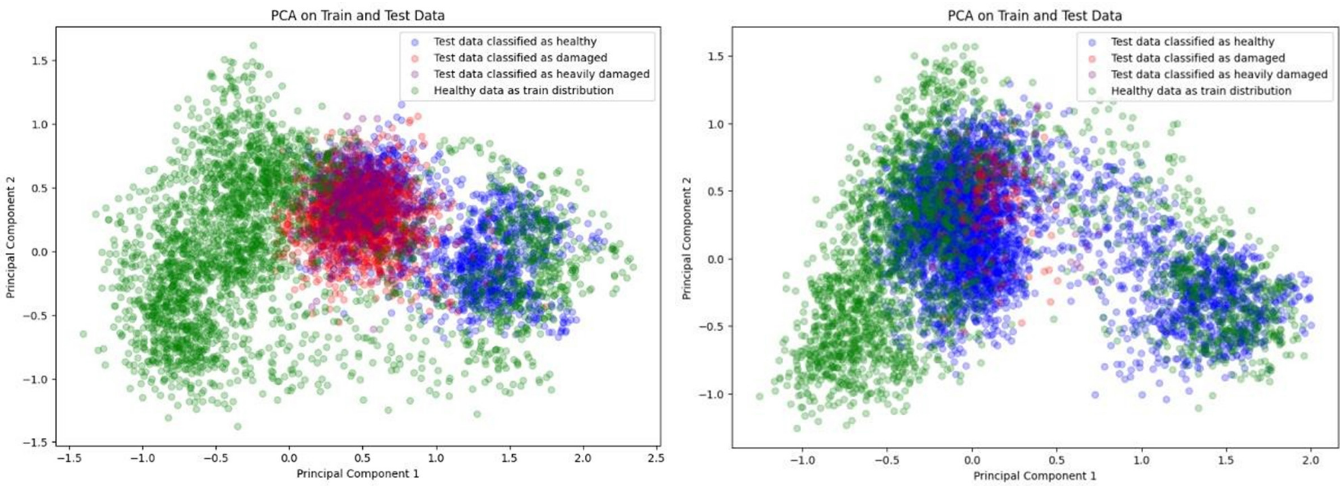

Figure 2: PCA of ADA Bridge Data is showcased in the comparison between a damaged condition on the left and an undamaged one on the right. The green dots denote the distribution of data in the ADA Bridge's healthy state. Test data is categorized into two groups: blue for healthy data and red for data predicted as damaged.

Figure 3 visually presents the damage index for each sensor, aligning with the depiction in Figure 1. While damage is detected by all sensors, its intensity is more pronounced at the actual site of occurrence. In every case, we can clearly discern the location where damage has occurred.

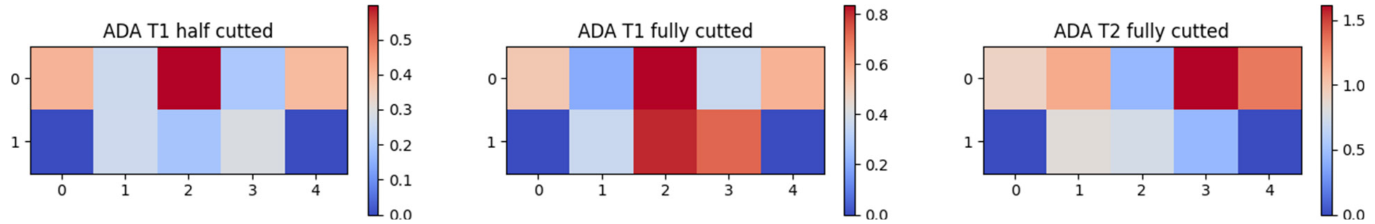

Figure 3: Damage index for each sensor.

Looking forward

MFCCs have shown their worth, but their inherent limitations stem from a static, handcrafted design. The necessity of manually selecting a few parameters introduces potential suboptimal choices for specific problems. To overcome these constraints, we are actively transitioning to the utilization of neural networks as feature extractors. This strategic pivot involves moving away from manual crafting, opting instead for automatically generated features that unlock the full spectrum of signal processing potential [6,7].

Conclusion

Our research demonstrates the transformative potential of unsupervised machine learning, particularly focusing on acoustic characteristics, in revolutionizing traditional methods of bridge health monitoring. By employing Mel-frequency cepstral coefficients (MFCC) as industry-standard features for speaker recognition, we redefine the monitoring paradigm, treating the bridge's acoustic patterns as its "voice." This innovative approach, coupled with the dynamic classification capabilities of a neural network, proves to be a robust and adaptable method for discerning healthy and compromised bridge conditions. The integration of MFCC with environmental measures enhances the comprehensiveness of our monitoring, allowing for a comparative analysis of the bridge's health dynamics across diverse conditions. The presented test case on the ADA Bridge in Japan further validates the efficacy of our methodology, showcasing its ability to accurately detect and localize damage. This research not only advances the field of structural health monitoring but also underscores the potential of machine learning in enhancing the safety and longevity of critical infrastructure.

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Conflict of Interest

In the spirit of transparency, it is essential to address any potential conflicts of interest that may arise from this research. The authors declare that, to the best of their knowledge, there are no conflicts of interest that could have influenced the design, implementation, or interpretation of the results presented in this study. We affirm our commitment to unbiased scientific inquiry and the dissemination of knowledge for the betterment of the field.

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