Chapter 15
Vehicle Load Identification of Bridges Using Acceleration Response Data

Iman Dabbaghchian and Shamim Pakzad

Abstract Identifying the characteristics of passing vehicles on the bridge, often referred to as weigh-in-motion (WIM) systems, is of interest in various applications of bridge maintenance and monitoring. WIM systems enable the measurement of vehicle weights, including the weight of individual axles, depending on the accuracy of the system, as they travel over the pavement. Following years of development, WIM systems are now capable of delivering detailed traffic information, including vehicle classification, axle and wheel weights, total gross weight, speed, and transit date and time. WIM systems also contribute to enhancing the safety evaluations of pavements and bridges. However, depending on the type of WIM systems, several obstacles must be addressed for these systems to see widespread adoption. These challenges include their high cost, the requirement for specialized technical knowledge, limited durability, and the need for ongoing inspection and maintenance. This study introduces an innovative method that can replicate a WIM system utilizing acceleration response data. The acceleration data is relatively easy and inexpensive to collect. By employing signal processing techniques, specifically wavelet transforms, this approach aims to extract and decompose the response signal to accurately determine the number, weight, and speed of passing vehicles on the bridge. This study digs deep into the dynamics of the bridge and its interaction with vehicles through case studies of moving vehicle loads with different weight classes, speeds, and directions. The uncertainty in the prediction is also discussed in the results.

Keywords Bridge load identification · Acceleration response data · Wavelet transform · Bridge health monitoring · Signal processing

Introduction

Structural health monitoring (SHM) of bridges is a critical task in ensuring the long-term safety, durability, and reliability of both the bridges themselves and the societies they serve. As vital components of transportation infrastructure, bridges not only facilitate the flow of goods and services but also play a significant role in economic and social stability. However, many of these structures are aging, particularly in the United States, where a large percentage of the nation's bridges were built more than 50 years ago. The American Society of Civil Engineers (ASCE) has reported that over 42% of U.S. bridges are at least 50 years old, with more than 46,000 deemed structurally deficient. These aging bridges are increasingly subject to material deterioration, environmental degradation, and heavier loads than originally designed for, which highlights the urgent need for continuous and precise monitoring systems.

The increasing volume of traffic, especially from overweight enforcement vehicles, exacerbates safety risks and presents additional maintenance challenges for transportation agencies, particularly on deteriorating bridge infrastructure or those under extreme cases. [1, 2] This can lead to significant damage to both the structural and non-structural components of the bridge, such as beams and pavements, causing issues like fatigue, cracking, and, in extreme cases, structural collapse. [3] Identifying and tracking the number of large vehicles and overall traffic volume can significantly assist bridge maintenance agencies in optimizing their maintenance strategies and ensuring the longevity and safety of the structure.

SHM systems rely on field measurement data, and dynamic acceleration response has been used for operational modal analysis (OMA) to extract modal characteristics such as natural frequencies, damping ratios, and mode shapes. These parameters provide insights into the global condition of the structure and are widely utilized in the assessment of bridge performance under both operational and extreme conditions [4, 5]. However, the use of accelerometers extends beyond

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Roland Platz et al. (eds.), *Model Validation and Uncertainty Quantification, Vol. 3*, Conference Proceedings of the Society for Experimental Mechanics Series, https://doi.org/10.13052/97887-438-0148-1_15

modal analysis, with their ability to capture high-frequency content offering new opportunities to extract additional features related to dynamic loads. Recently machine learning methods have also retained a lot of attention, and multiple applications have been done with the combination of artificial neural network and acceleration data [6, 7, 8, 9, 10]

Recent advances in signal processing techniques, particularly the application of wavelet transforms, have provided sharper time-frequency resolution, enabling the identification of high-frequency content that is often obscured by noise [11, 12, 13]. Wavelet-based approaches have shown significant potential in capturing transient events, such as vehicle-induced loads, which traditional Fourier-based methods may fail to detect effectively, especially in noisy and non-stationary signals [14, 15]. Identifying the dynamic loads, such as the moving vehicles on bridges, provides valuable information about the structure's response to real-time loads. This information can be used to improve load modeling, enhance predictive maintenance strategies, and optimize load distribution for bridge management systems [16, 17]. Moreover, accurate identification of vehicle trajectories and weights can support the development of more robust load-rating systems, contributing to the structural integrity of bridges under varying traffic conditions.

In this paper, we present a novel framework for extracting vehicle trajectories on bridges by leveraging the high-frequency components of acceleration data derived from wavelet transform analysis. The proposed methodology effectively captures the dynamic interaction between vehicles and the bridge structure. The accuracy and robustness of the framework are validated through multiple numerical simulations, demonstrating its potential for real-time bridge monitoring and load identification.

Methodology

The proposed methodology begins with the acquisition of acceleration data from multiple locations along the bridge structure. This data is then utilized to detect and characterize the dynamic input load, specifically aiming to identify or estimate critical parameters of the passing vehicles, such as their weight and speed. To demonstrate the effectiveness of this approach, a detailed case study is conducted using a numerical simulation of a two-dimensional steel truss bridge. This simulated model is based on a real-world bridge located in Pennsylvania, USA, providing a realistic and practical context for the analysis.

Let $a_i(t)$ represent the acceleration response signal from location i, where t is time and $i = 1, 2, \ldots, M$ and the signals are obtained from M locations at a sampling frequency of f_s Hz. For each signal $a_i(t)$, we select a time window T_w of length Δt (e.g., 30 seconds) and compute its synchrosqueezed wavelet transform (SWT). The SWT produces wavelet coefficients $W_i(t, f)$ as a function of time t and frequency f, which can be written as:

$$W_i(t, f) = \text{SWT}(a_i(t), f_s) \tag{1}$$

where $W_i(t, f)$ represents the wavelet coefficients of the signal $a_i(t)$ at time t and frequency f. Also, the frequency range for the wavelet coefficients will be from 0 to the Nyquist frequency which is $f_s/2$. However, the maximum frequency can be cut off to a lower value of interest, depending on the modal characteristics of the structure. The frequency range $[0, f_{\text{max}}]$ is then divided into N segments, each with a width of $\Delta f = \frac{F_{\text{max}}}{N}$. For example, if $f_{\text{max}} = 20$ Hz and $N = 8$, the frequency bands are defined as:

$$F_n = [(n-1)\Delta f, n\Delta f], \quad n = 1, 2, \ldots, N \tag{2}$$

Thus, for $N = 8$, the intervals are $[0, 2.5], [2.5, 5], \ldots, [17.5, 20]$ Hz. For each frequency band F_n, the wavelet coefficients $W_i(t, f)$ are averaged across the frequency range to obtain a new time signal $A_i^n(t)$, defined as:

$$A_i^n(t) = \frac{1}{\Delta f} \int_{F_n} W_i(t, f)\, df \tag{3}$$

where $A_i^n(t)$ represents the averaged wavelet coefficient for location i in the n-th frequency band. For each frequency band F_n, a moving average is applied to the wavelet coefficients $A_i^n(t)$ using a window of length Δt_m (e.g., 1 second), with an overlapping shift Δs_m (e.g., 0.5 seconds) for smoothing purposes. The smoothed signal $\bar{A}_i^n(t)$ is given by:

$$\bar{A}_i^n(t) = \frac{1}{\Delta t_m} \int_{t-\Delta t_m/2}^{t+\Delta t_m/2} A_i^n(\tau)\, d\tau \tag{4}$$

where Δt_m is the moving average window length, and Δs_m is the time shift applied between successive windows.

After processing the signal in the current time window, we shift the window by s seconds and repeat the analysis. If the initial window starts at t_0, the k-th shifted window will begin at $t_0 + ks$, where s is the shift step. The process is repeated for each time window, producing a series of smoothed wavelet coefficients for each frequency band.

$$\bar{A}_i^n(t_0 + ks) \quad \text{for} \quad k = 0, 1, 2, \ldots \tag{5}$$

By generating a series of smoothed wavelet coefficients for each frequency band and aligning the signals corresponding to each location with their respective positions on the structural joints (mapping the geometry), a heatmap can be produced that effectively visualizes the trajectory of vehicle movement across the bridge.

Analysis

To illustrate the effectiveness of the proposed method, a numerical example is presented and the corresponding results are discussed in detail. The example involves a finite element analysis (FEA) of a two-dimensional bridge subjected to moving loads, which is representative of real-world conditions. The simulation uses standard AASHTO vehicle configurations to model the dynamic interaction between the bridge and the passing traffic. In the first scenario, three trucks are introduced: two traveling in the direction from sensor S1 to S16 at the speed of 18.3 m/s (60 ft/s), while the third truck moves in the opposite direction at the speed of 16.8 m/s (55 ft/s). This mixed traffic flow provides a robust test case to evaluate the response of the bridge under varying load conditions. Figure 1 illustrates the geometry of the 2D bridge model and presents the vertical acceleration response at each joint along the structure, as captured during the moving load analysis. By analyzing these acceleration responses, we can further assess the method's capability to detect and estimate the input parameters such as vehicle weight and speed, based on the bridge's dynamic response.

The collected responses from 16 locations have a sampling frequency of 100 Hz, which means the observability of the frequency content is 50 Hz. Figure 2 shows the magnitude of the wavelet coefficients. Even from these figures, it can be observed that the high-frequency content is moving across the spatial and temporal domain. The main contribution of this work is to introduce how these high-frequency contents can be traced and analyzed.

The synchrosqueezed wavelet transform [13] is a time-frequency analysis method that is useful for analyzing multicomponent signals with oscillating modes and was aimed to sharpen the time-frequency representation. The primary difference between the synchrosqueezed wavelet transform (SWT) and the regular wavelet transform lies in their time-frequency representation and the precision of frequency localization. The regular wavelet transform provides a time-frequency analysis where the frequency resolution decreases with higher frequencies, and the result is a multi-resolution analysis with non-uniform frequency bands. In contrast, the synchrosqueezed wavelet transform enhances the frequency resolution by "reassigning" the wavelet coefficients closer to their actual frequency. This process leads to a sharper and more concentrated time-frequency representation, which is particularly useful for separating closely spaced or overlapping frequency components in non-stationary signals. Essentially, the SWT aims to recover a finer frequency detail, which the regular wavelet transform lacks, making it a more precise tool for analyzing signals with varying frequencies over time.

Following the calculation of the wavelet magnitude coefficients, the time-frequency representation was divided into eight distinct frequency bands. For each band, the wavelet magnitudes were averaged, resulting in eight distinct averaged magnitude signals for each measurement location. To further refine these signals, a moving average smoothing technique, as detailed in the methodology section, was applied to reduce fluctuations in the wavelet magnitudes and produce smoother time-frequency representations. Subsequently, the averaged magnitude signals from the 16 sensor locations (S1 to S16) were spatially aligned to construct a series of spatial-temporal maps. Specifically, the signals from each location were placed adjacently, producing eight separate maps corresponding to the eight frequency bands (see Figure 3). In these maps, the x-axis represents time, while the y-axis corresponds to the spatial arrangement of the bridge, with locations S1 to S16 aligned according to the horizontal coordinates of the structural joints. The z-axis captures the average wavelet magnitudes.

This approach enables a clearer representation of both the spatial and temporal domains of the signal, allowing for a more comprehensive analysis of dynamic responses across the structure. The visualized heatmaps thus provide a detailed perspective on the variations in wavelet magnitudes across different frequency bands and locations, facilitating the identification of key patterns, such as vehicle movement trajectories on the bridge.

In Figure 3, the plots corresponding to the first five frequency bands (0 to 12.5 Hz), which encompass the frequency range associated with the first 20 structural modes, do not exhibit a discernible trajectory pattern for the passing vehicles. This indicates that within these lower frequency bands, the vehicle-induced dynamic responses are likely dominated by modal contributions that obscure any clear indication of the moving loads. In contrast, the plots corresponding to the higher frequency bands—specifically the last three bands—clearly reveal the trajectory of the vehicles as they traverse the bridge. These higher frequency bands capture the localized dynamic effects of the moving loads, which are less influenced by the global modal behavior, thereby allowing the vehicle trajectories to be distinctly visualized in the time-frequency domain.

The clear distinction between the results in the lower and higher frequency bands emphasizes the importance of selecting appropriate frequency ranges when conducting moving load analyses. The ability to capture the vehicle trajectory is crucial for accurately assessing the dynamic interaction between the vehicles and the structure. By focusing on the higher frequency

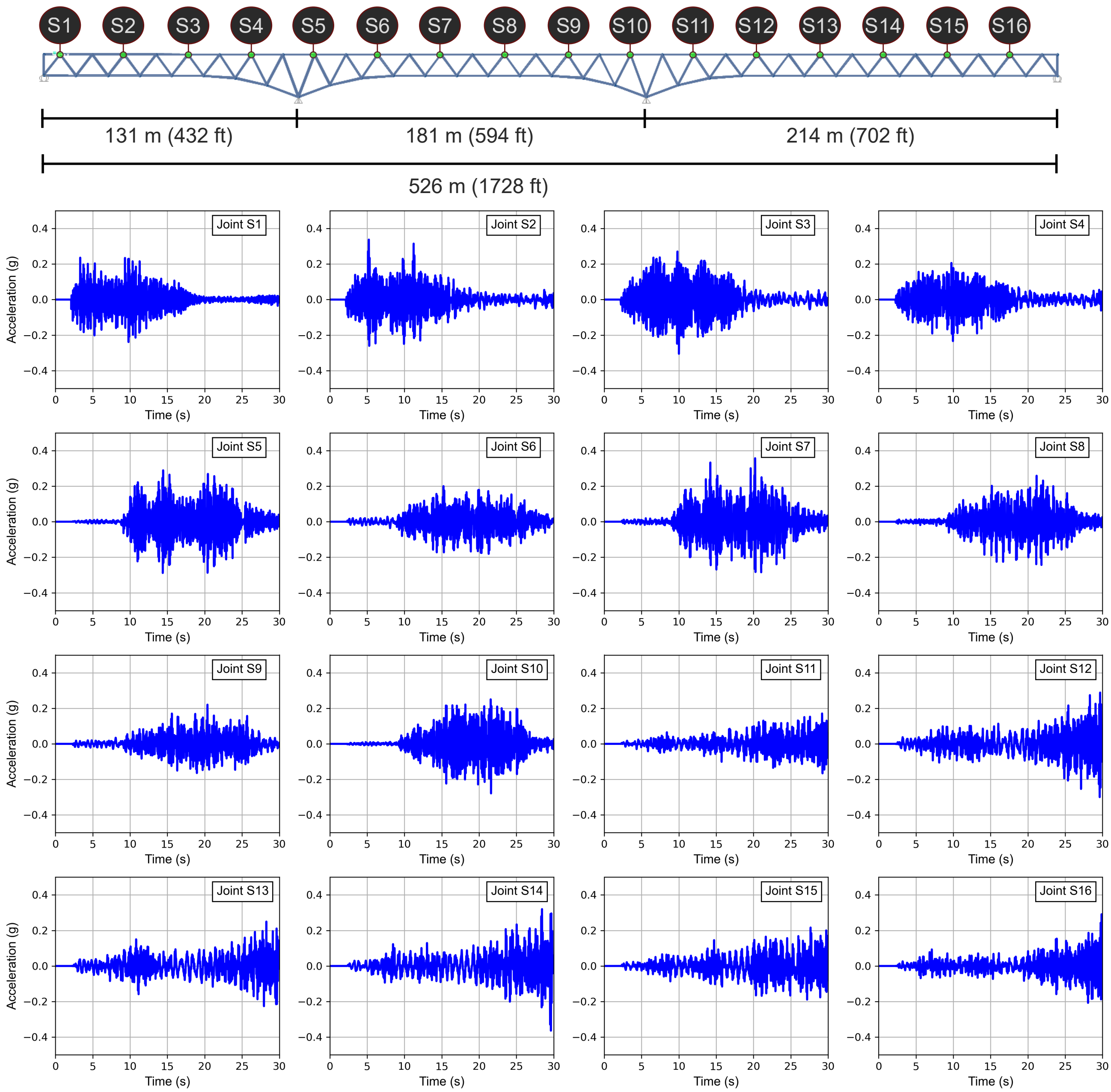

Fig. 1 Vertical acceleration response signals from 16 joints along the bridge deck position under the moving load with three vehicles. The bridge geometry and joints coordinates are also shown at the top.

components, the trajectory maps provide valuable insights into the localized structural response to the moving loads, which is essential for understanding the dynamic behavior of the bridge under vehicular traffic.

The final frequency bin provides the most accurate estimation of vehicle trajectories, demonstrating that higher frequency bands yield better precision in identifying vehicle characteristics. In the spatio-temporal visualization of averaged wavelet magnitudes shown in Figure 3, the magnitude of the wavelet coefficients is indicative of the vehicle's weight, while the slope of the trajectory lines correlates with the vehicle's speed. Based on these observations, the final frequency bin was selected and further refined using interpolation techniques to enhance the resolution of the trajectory estimates. These refined estimates were then compared to the ground truth from the moving load analysis involving three vehicles, as presented in the top two plots of Figure 4. The results show a high degree of accuracy, with the vehicle trajectories being clearly and distinctly identified.

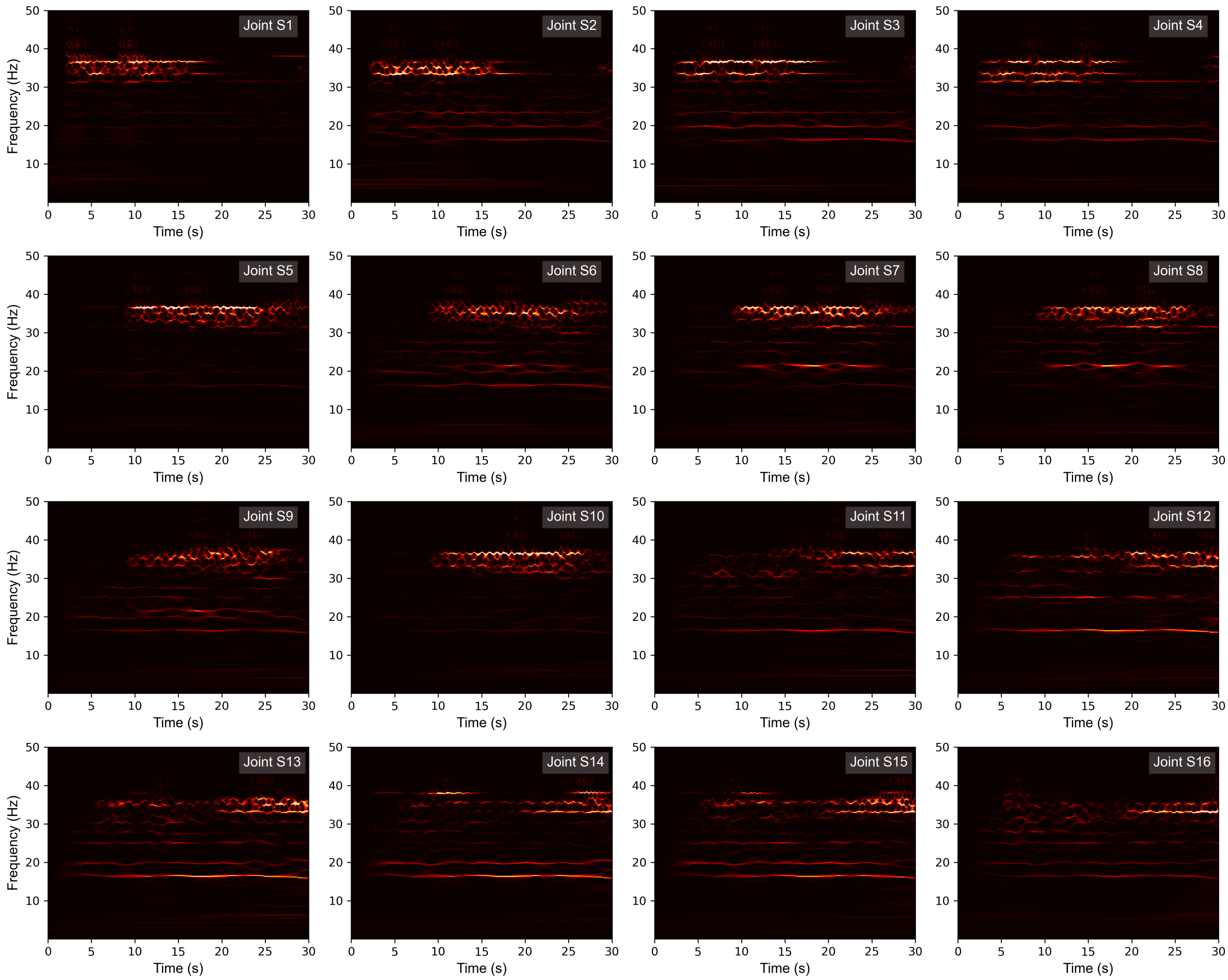

Fig. 2 Wavelet transform coefficient on the acceleration response signals from 16 joints.

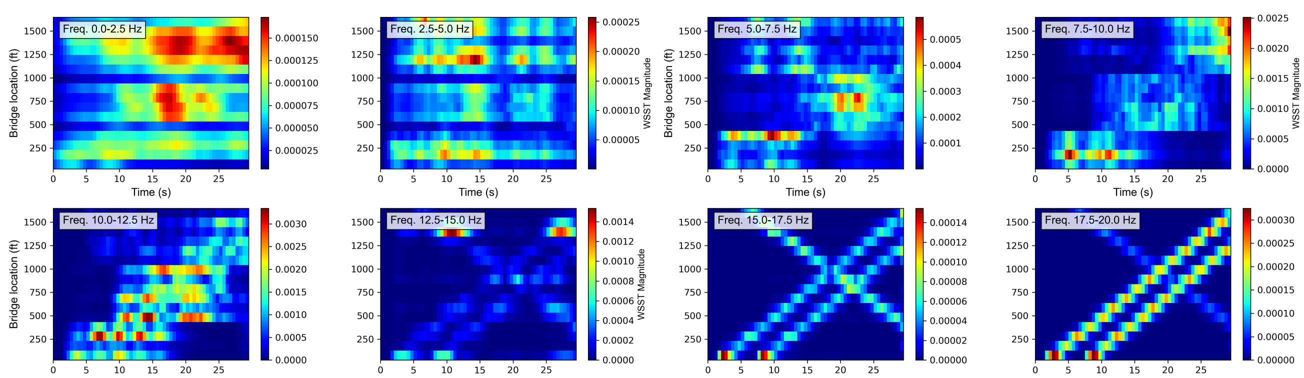

Fig. 3 Spatio-temporal visualization of the averaged wavelet coefficient magnitudes for eight distinct frequency bins, with sensor locations mapped to their corresponding positions on the bridge structure.

The bottom two plots of Figure 4 present the results of a more complex moving load scenario, involving nine vehicles simultaneously traversing the bridge over a 60-second time horizon with speeds from 29 to 80 m/s and weights from 72 to 330 kips. This case presents a significant challenge for conventional methods in detecting moving loads due to the complexity

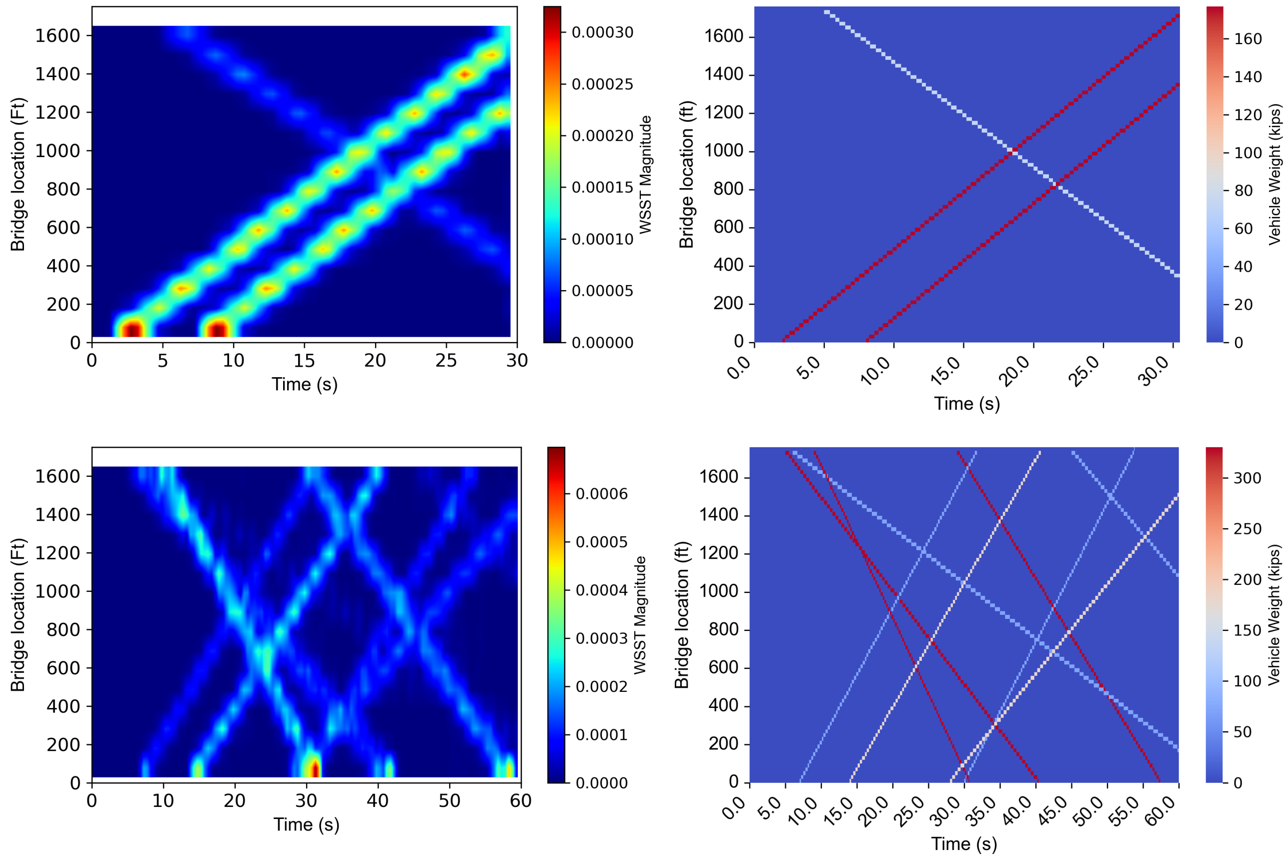

Fig. 4 Vehicle trajectory maps.Top left: Identified vehicle trajectory maps using wavelet coefficients with three vehicles on the bridge, Top right: The true trajectory map of the moving load case with three vehicles on the bridge. Bottom left: Identified vehicle trajectory maps using wavelet coefficients with nine vehicles on the bridge, Bottom right: The true trajectory map of the moving load case with nine vehicles on the bridge

of multiple vehicles interacting with the structure. However, the proposed framework successfully identified the majority of the vehicle trajectories, even under these complex conditions. It is worth noting that in this second analysis, some vehicle trajectories appear faded, which suggests that the ability to distinguish between vehicles may be reduced when vehicles of significantly different weights are present on the bridge. This reduction in resolution is a point for future investigation, as improving the signal quality in such cases could further enhance the precision of vehicle identification.

The quality of the collected signals plays a critical role in the effectiveness of the proposed framework, particularly when dealing with high-frequency components, which are often contaminated by noise. As high-frequency content is more susceptible to interference, it becomes essential to assess the signal-to-noise ratio (SNR) and ensure that the quality of the recorded data is sufficient to distinguish meaningful structural responses from noise. Establishing the quantitative limitations of this method requires further investigation, taking into account factors such as sensor quality, the dynamic characteristics of the bridge, and the environmental conditions under which the data is collected. A systematic evaluation of these factors will determine the feasibility of applying this framework to specific bridge monitoring scenarios.

As advancements in sensor technology and signal processing techniques continue to improve, the ability to extract detailed information from acceleration data will significantly enhance. This framework has the potential to leverage these improvements, making it a promising approach for the identification of vehicle-induced loads and dynamic interactions on bridges.

Figure 5 presents the vehicle trajectory maps derived from signals with varying SNR levels of 20 dB, 30 dB, and 50 dB. The case study results demonstrate that at an SNR of 20 dB, the quality of vehicle identification decreases, with reduced clarity in the vehicle trajectories. Nevertheless, two vehicles remain clearly identifiable, indicating that the method retains some robustness even at lower signal quality. At SNR levels of 30 dB and 50 dB, the quality of identification improves significantly. At 30 dB, the identification quality is satisfactory, while at 50 dB, the method provides excellent accuracy,

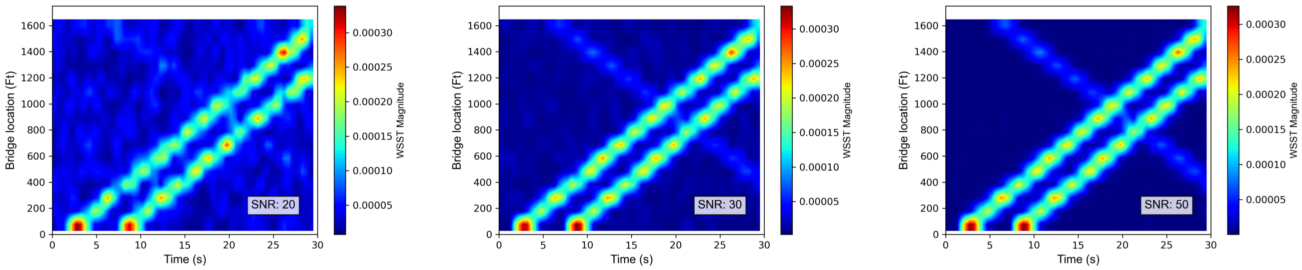

Fig. 5 The identified vehicle trajectories when the input acceleration responses are polluted to noise with three different SNR levels of 20, 30, and 50 dB.

with the vehicle trajectories being sharply defined. These findings highlight the sensitivity of the method to signal quality and underscore the importance of ensuring high SNR in field applications for optimal results. Moreover, incorporating uncertainty quantification in these assessments will allow for a more rigorous evaluation of the method's performance across different SNR levels, providing confidence in the robustness of the approach under various noise conditions.

Conclusion

This paper presents a novel approach for bridge load identification using an array of acceleration responses collected along the bridge length. While acceleration data is traditionally employed for operational modal analysis and extracting modal characteristics, this study demonstrates that additional valuable features can be derived. The high-frequency content of the signal was extracted using a wavelet transform, providing a sharper and more detailed time-frequency representation. Through subsequent signal processing, vehicle trajectories traversing the bridge were identified with high accuracy, along with indications of vehicle weights.

Accelerometers are well-suited for this application due to their ability to capture high-frequency content, particularly when high-quality models are used. They are also cost-effective compared to other sensing technologies, making them ideal for large-scale applications. Although accelerometers are susceptible to certain types of noise, they are generally robust against electromagnetic interference, with proper noise reduction techniques and sensor placement necessary to ensure measurement accuracy. Nevertheless, further investigation is needed to assess the impact of noise on high-frequency content and its relationship with the dynamic characteristics of the bridge structure. This will help clarify the limitations of the proposed method and enhance its applicability.

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