Deconvolution of Contaminated Acceleration Signals Recorded via Moving Sensors on Bridges

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Abstract. Bridge modal properties can be identified upon processing of instrumentation measurements (primarily accelerations). The required data processing is typically easily manageable compared to the deployment efforts. Consequently, moving sensors are becoming more desirable and feasible as more sophisticated algorithms mature. Sensors (accelerometers) mounted on moving vehicles detect a combination of vibration responses as they drive by bridges. The resulting vehicle vibrations are produced by several interacting excitations, such as bridge vibration, road surface roughness, and vehicle-induced vibrations. So, the measured accelerations are contaminated by these sources and cannot be assumed to be inherent to the bridge. As such, a proper understanding of the dynamic vehicle-bridge interaction phenomenon is essential. Several algorithms and processes must be implemented to obtain a denoised bridge signature signal suitable for modal identification purposes. An integrated algorithm for performing vehicle response deconvolution is introduced. This novel algorithm combines the previously published algorithms for vehicle response deconvolution, the frequency response function (FRF), and the ensemble empirical modal decomposition (EEMD). The hybrid algorithm (FRF+EEMD) is benchmarked against the individual FRF and EEMD algorithms. The hybrid algorithm outperforms both counterparts in signal denoising.

Keywords: Ensemble Empirical Modal Decomposition (EEMD) · Frequency Response Functions (FRF) · Source Separation · Structural Health Monitoring (SHM)

1 Literature Review

Since modern transportation networks significantly rely on bridges for connectivity and serviceability, maintaining bridges in a sustainable state of repair is essential. However, due to repetitive traffic loads, environmental factors, or normal aging, bridges are subject to ongoing structural deterioration. The bridge's structure may sustain slight damage from ongoing exposure to heavy vehicle loads, rain, and other natural occurrences [1]. If safety precautions are not taken, these damages over time may compound and result in minor deformations in the bridge, eventually leading to collapse. Thus, it's crucial to regularly and effectively check on the bridge's structural condition as deterioration

happens over time. Thanks to innovative data collection methods and cutting-edge sensor technology, the civil engineering community has been aided to more frequently and precisely monitor the condition of bridges [2].

In order to better understand the dynamic properties of the bridge, structural health monitoring systems frequently use acceleration data from the oscillations of the bridge. The main causes of these vibrations are normal traffic and environmental loading. Measuring and calculating the bridge's dynamic properties, which are impacted by any harm to the mechanical structure of the bridge, is a prominent method of determining and locating the deterioration of the bridge [3]. Given this, a number of characteristics, including mode shapes [4], natural frequencies [5, 6], and damping ratios [7, 8] can serve as indications for determining the damage to the bridge. These variables belong within the structural system identification (SID) category, which scholars have explored using a variety of methods [9–11].

Moving sensors arise as an alternative to using fixed sensor networks. It is essential to emphasize that the data collected via the drive-by method is fundamentally distinct from the data collected by fixed sensor networks, necessitating unique considerations [12]. To correctly identify the bridge's structural dynamics using moving sensors, it is necessary to consider a number of important parameters. These include the vehicle's speed, the frequency ratio between the bridge and the vehicle, and the acceleration amplitude ratio [13]. Several other bridge-related characteristics, such as span length and road surface roughness, can also alter the readings from the moving sensor [14, 15]. All of these characteristics influence the vehicle bridge interaction (VBI), which may be seen as a combination of two distinct sets of model features. The first category comprises vehicle parameters such as loading circumstances and vehicle construction. The second category pertains to bridge factors such as road conditions and the bridge's structural system.

The literature studies on Vehicle Bridge Interaction (VBI) models are extensive [16, 17]. These models are essential in study fields such as moving load bridge response [18–20], moving load identification issue [21–24], experimental case studies [25], and direct topic research. Due to the enormous number of (often unknown) factors, the complexity of these models is inherent. Sadeghi Eshkevari et al. [2, 26] presented a simple model for analyzing bridge-vehicle interaction for bridges with medium to large spans under random traffic loads. This approach divides the coupled interaction into two independent subproblems. The first involves sensors exposed to a linear superposition of bridge response and road roughness, while the second involves the determination of the bridge's dynamic characteristics under random stimulation. It has been shown that the suggested approach increases computing efficiency with low error. This study focuses on medium- to long-span bridges, and so this simplified model is used.

2 Research Significance

In proportion to the development of mobile sensor networks during the last several years, the SHM algorithms demand substantial developments. Developed SHM systems could contribute significantly to recent advances in structural engineering applications pertaining to the assessment of structures under seismic [27–39] and wind [40–44] effects.

This study contributes to the development and implementation of more efficient algorithms for sensor networks. The work described here focuses on gathering vibrational measurements from moving sensors and then processing them for source separation. This study introduces a new hybrid module that combines ensemble empirical mode decomposition (EEMD) and frequency response function (FRF) for the removal of vehicle dynamics from the detected signals. After completing this stage, the residual signal reflects the bridge's vibrational response and road roughness, which may be further analyzed to detect the bridge's natural frequencies.

3   Removal of the Vehicle's Dynamic Response

Regarding the vehicle's dynamic response, Ensemble Empirical Mode Decomposition (EEMD) and Frequency Response Function (FRF) may remove this signal component. If the vehicle's dynamic attributes are unknown, EEMD may be used to break the original signal into numerous Intrinsic Mode Functions (IMFs), then remove the vehicle's dynamic properties from the signal. Alternately, if the dynamic properties of the vehicle are established, its FRF may be created. Then, using this FRF, frequency deconvolution may then be done on the original data to remove vehicle dynamics.

Using Empirical Mode Decomposition (EMD), a nonstationary and nonlinear signal might be decomposed into several intrinsic mode functions (IMF). The technique for the iterative extraction of IMFs by EMD is known as the sifting algorithm. By superposing the IMFs with the residual, it is possible to recreate the original signal. To prevent mode mixing, Gaci [45] proposed the EEMD algorithm, which incorporates random white noise into the signal. Each iteration generates a new noise signal that has no association with the accompanying IMFs. For vehicle response removal, the IMFs associated with vehicle response may be eliminated [2]. The IMFs with traces of natural vehicle frequencies are eliminated, and the remainder IMFs are overlaid.

Using the vehicle's frequency response function (FRF) to deconvolve the recoded signal and derive the input signal is another way to eliminate vehicle dynamics. The disadvantage is that the vehicle's attributes must be known, either by manufacturer-supplied information or system identification. The vehicle may be simplified by modeling it as a 2DOF system (also known as the quarter-car model) [46]. The quarter-car model includes both spring-loaded and unsprung masses. The unsprung mass consists of the mass of the vehicle's wheels, suspension system, and its directly attached components. While the sprung mass represents the vehicle's body supported by the suspension system and its components.

For such a system, the equilibrium equation can be transformed into the frequency domain $(i\omega)$ [47], to be represented as follows:

$$\{X(i\omega)\} = [H(i\omega)] \cdot \{F(i\omega)\} \tag{1}$$

where $\{X(i\omega)\}$ and $\{F(i\omega)\}$ are the displacement and force vectors in the frequency domain, respectively, while $[H(i\omega)]$ is the FRF component that relates the external force to the system response. The FRF can be computed using the formula given in Eq. (2) [48].

$$H_{jk}(\omega) = \sum_{r=1}^{N} \frac{\Phi_{rj} \cdot \Phi_{rk}}{\omega_r^2 - \omega^2 + 2i\omega\omega_r\xi_r} \tag{2}$$

where j and k represent the indices at the input and output DOFs, respectively, for a specific frequency (ω). While Φ is the mode shape matrix with N modes. ω_r and ξ_r are the undamped natural frequency and the damping ratio of mode r.

4 Simulation Setup

A finite element model of a 500-m single-span bridge was used as a testing model to evaluate the validity of several algorithms for various road profiles. The employed 2D basic beam model was discretized using 10,000 DOFs with mass and stiffness parameters to provide modal properties that are realistic and more prevalent for medium to long-span bridges [2, 8]. The frequencies of the first four fundamental modes were 0.1357 Hz, 0.3714 Hz, 0.7213 Hz, and 1.1710 Hz, with damping ratios of 2.0%, 0.8%, 0.6%, and 0.6%, respectively. To mimic traffic situations, distinct load vectors of white noise were applied to each DOF. The simulation lasted 400 s, and the sampling rate was 50 Hz.

A quarter-car model with 2 DOFs was selected from the literature to be implemented in the simulation. The model was introduced by Sadeghi Eshkevari et al. [2] and had two fundamental frequencies of 5.14 Hz and 36.78 Hz. To analyze the algorithms, four road surface roughness patterns are studied. First, roads of expansion joints (EJ) every 60 m with 0.5-m-wide dips. As a signal, the expansion joints will represent impulses that the vehicle will be subjected to every specified interval (60 m). The second is the ISO surface roughness of the road profile [49]. Road profiles can be categorized based on criteria set defined by ISO 8606 [49] to facilitate comparison and assessment of vertical road profile roughness. ISO grade C is used for profile comparisons. The third instance is a straightforward sinusoidal function with two frequencies (3.5 Hz and 7.1 Hz). The final instance is a random white noise profile with equivalent intensities across all frequency bands.

After computing the bridge response, a 2D matrix containing the bridge response is generated. In this instance, however, the spatial profile of the bridge at each time station is distinct. Vehicles start traveling over the bridge at various beginning places; hence, the same piece of the bridge is traversed at different times by cars. According to the estimated vehicle speed, the road profile acceleration observed by the vehicle is calculated and filled along the bridge response matrix. Then, based on the beginning position and speed of each vehicle, its base excitation input is determined (bridge and road acceleration). Then, simply, the response of the vehicle is calculated and used to represent the sensor reading.

5 Results and Discussions

As previously established, if the vehicle's properties are known, its natural frequency may be calculated, and using FRF, the vehicle's contribution to the signal can be eliminated. As indicated in Fig. 1, this was completed for each of the four road profile scenarios. There is a distinct reduction in the vehicle's natural frequency (5.14 Hz) for all road profiles, while the road roughness component remains unaltered. Nonetheless, this results in a change in the amplitude of the total signal, as seen by the variation in amplitudes at frequency peaks. This inaccuracy (change in amplitude) may not impact the accuracy of frequency

content detection for a signal captured by a single vehicle. While, in the future, for a comprehensive assessment of a bridge's modal features, the source-separated readings from various vehicles will be used to create a sparse observation matrix. If these vehicles have different dynamic properties, there will be significant signal amplitude changes, which will be introduced as noise.

EEMD may be used to determine the IMFs of a signal for a vehicle with unknown properties. Each signal was decomposed into six components. IMFs can be sorted according to dominant frequencies. Excluding some IMFs and then recombining the rest of the components can lead to a new signal with some properties filtered out. By inspection, it was found that the first three IMFs should be excluded to eliminate vehicle dynamics. As demonstrated in Fig. 2, removing the first three IMFs and recombining the remainder would result in signals with bridge and road roughness components and essentially no vehicle component. Compared to the FRF approach, EEMD effectively eliminates vehicle components while maintaining the same amplitude of the bridge's natural frequencies. However, some road profile frequencies are also eliminated since they were included in the first three IMFs. This is shown by the sinusoidal road roughness. Compared to FRF, EEMD dramatically decreased road roughness-induced frequencies. This is due to the fact that a portion of them join the first three IMFs, which are deleted.

According to the FRF findings, the output after frequency deconvolution does not have the same frequency amplitudes as the bridge, but these amplitudes remain unaffected in the EEMD output. In contrast, FRF has shown superior performance when it comes to removing a vehicle component without affecting the other components. In other words, FRF detects the frequency content of a vehicle with more accuracy, but it impacts the remaining signal's amplitudes. To combine the benefits of both techniques, a hybrid approach was tested, and results were plotted, as shown in Fig. 3.
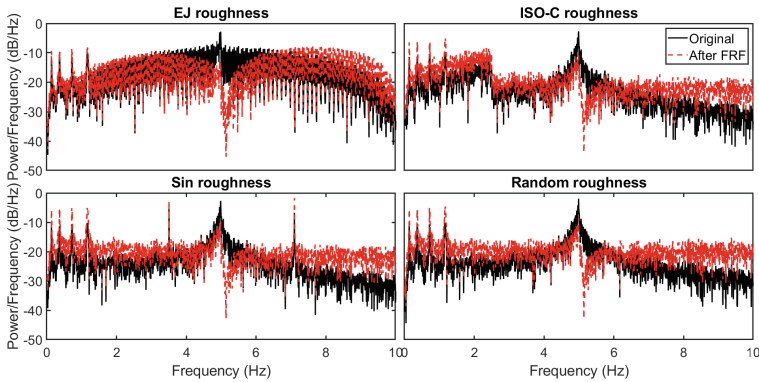

Fig. 1. Removing vehicle dynamics through frequency deconvolution.

In the hybrid approach, the vehicle component is filtered out using both methods (FRF and EEMD) to have two purified signals (S-FRF and S-EEMD). S-FRF is accurate in terms of frequency content but not amplitude. Thus, scaling of S-FRF amplitudes could enhance its overall accuracy. Therefore, the maximum amplitude of S-EEMD in the frequency domain was used to scale S-FRF. The output signal is a scaled version
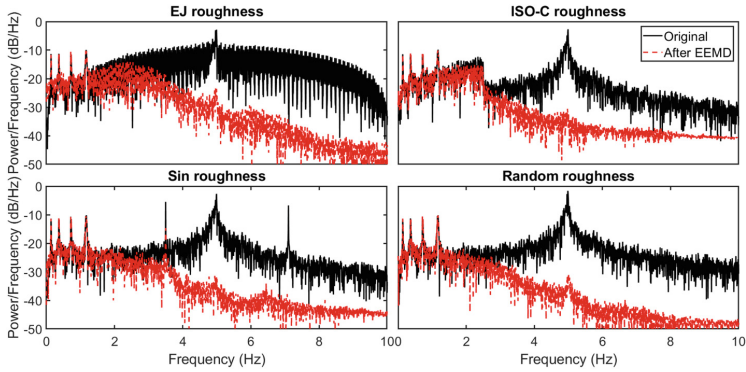
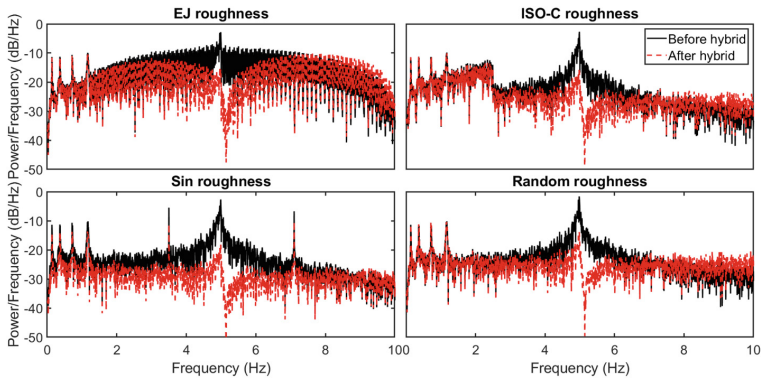**Fig. 2.** Removing vehicle dynamics through EEMD.

Fig. 3. Removing vehicle dynamics with the hybrid method.

of S-FRF with the same maximum frequency content amplitude as S-EEMD. Figure 3 displays these findings. As seen in Fig. 3, this method allows for the detection of the bridge's inherent frequencies while eliminating car dynamics properly.

6 Concluding Remarks

An innovative hybrid algorithm for vehicle signal deconvolution has been introduced. In addition, comparative studies were conducted, and the following findings can be taken:

- The FRF approach for vehicle response deconvolution is very effective in isolating the frequency content of the vehicle. Nonetheless, it affects the amplitudes of the natural frequencies of the bridge.
- Unlike FRF, the EEMD approach maintains the amplitudes of the bridge response component in the recorded signal. However, it may delete certain frequency components irrelevant to the vehicle's contribution to the signal.
- The hybrid method, including FRF and EEMD, outperformed the EEMD and FRF algorithms individually, particularly for road profiles with random roughness.

Data Availability Statement. All models and codes generated or used during the study are available from the corresponding authors upon reasonable request.

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