Enabling Robustness to Vehicle-Bridge Variability in Drive-By Bridge Health Monitoring through Physics-Informed Signal Decomposition

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ABSTRACT

Bridge health monitoring (BHM) is important due to its benefits in detecting and diagnosing potential damages to bridges, providing early warning signals, and guiding maintenance decisions. Compared to manual inspection and fixed-sensors-based monitoring, drive-by BHM leverages vibration responses measured from vehicles passing over bridges to indirectly diagnose bridge damages, offering a rapid, mobile, and economical complementary solution. However, vehicle-bridge interaction (VBI) systems have large variations in bridge configurations, vehicle suspension systems, driving speeds, and so on, making it challenging to develop a damage diagnosis algorithm that is robust to vehicle-bridge variability. Moreover, existing approaches often require vehicle speed within a specific range to provide both informative and reliable signals, limiting their practical applications.

To address these challenges, we introduce a damage diagnosis approach that extracts damage-sensitive features and enhances their robustness to vehicle-bridge variability through physics-informed signal decomposition. Our approach first pre-processes and decomposes the vehicle vibration signal using the synchro-squeezed wavelet transform (SWT) because of its anti-noise property and its ability to represent the non-stationary and time-varying signals from drive-by vehicles. Then, a damage-sensitive signal is reconstructed using the inverse SWT within a physics-informed frequency band which excludes the vehicle and bridge resonances while keeping the damage-sensitive information. Peak features, such as peak location and energy, are input to the Gaussian Mixture Model clustering algorithm for diagnosing bridge damage in an unsupervised fashion. The performance of the proposed approach is evaluated on a numerical VBI model, which includes three vehicle types, six bridge lengths, and three bridge cross-sections, and takes into consideration the variability in vehicle properties and speed. The results validate that the extracted features are damage-sensitive and robust to various vehicle-bridge systems, achieving an overall mean absolute percentage error of 0.78% for damage localization and 13.13% for damage quantification.

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INTRODUCTION

Bridge health monitoring (BHM) enables us to send out early warning signals for bridges under abnormal health conditions and guides maintenance, repair, and management decisions. Currently, bridge assessment is mainly conducted by manual inspection and conventional fixed-sensor-based BHM, but both methods have limitations. Manual inspection can be costly and subjective as it relies on specific engineers for regular assessments, while fixed-sensor-based BHM is generally inefficient due to the high labor costs, economic expenses, and potential traffic disruptions [1]. To overcome these limitations, drive-by BHM was introduced to offer a mobile, scalable, and economical solution since each vehicle can be utilized for multiple bridges without additional sensor installation or manual labor on every bridge [2, 3].

Previous works on drive-by BHM can be mainly categorized into modal parameters extraction and data-driven methods [4]. Existing modal-parameter-based approaches mainly focused on modal frequencies and damping ratios [2, 5]. However, these approaches have limitations in accurately identifying the location and extent of damage because modal frequencies and damping ratios can be influenced by both damage and environmental and operational conditions. Alternatively, mode shapes and their curvature have been proposed as potential damage-sensitive parameters. However, they are also sensitive to noise and require high spatial resolution of the measurement, which increases the complexity of the damage identification process [6].

Data-driven and machine-learning methods have emerged as effective alternatives to modal-parameter-based approaches for damage localization and quantification, with various damage-sensitive features being proposed [7]. Nevertheless, one main limitation of these methods is the requirement for a sufficient labeled training dataset, which can be difficult to obtain due to the scarcity of damaged bridges in the real world.

To this end, the combination of data-driven and physics-based approaches can lead to effective damage diagnosis by integrating physics laws and constraints into signal processing and machine learning methods [4]. However, existing works are insufficiently robust in addressing the variability of vehicle-bridge systems, including different vehicle and bridge configurations and properties. Moreover, these approaches often rely on a specific range of vehicle speeds to generate informative and reliable signals, which may pose practical challenges in their implementation.

To tackle the aforementioned challenges, we introduce a new damage diagnosis approach robust to vehicle-bridge variability for drive-by BHM based on physics-informed signal decomposition. Specifically, the vehicle vibration signal is initially pre-processed and decomposed in the time-frequency domain to track the vehicle location using synchrosqueezed wavelet transform (SWT). SWT is chosen because of its ability to effectively capture non-stationary and time-varying signals produced by drive-by vehicles, as well as its anti-noise capability. Then, a damage-sensitive signal is reconstructed by computing the inverse SWT of the decomposed time-frequency signal within a specific frequency band informed by the physics derivation of the vehicle-bridge interaction (VBI) system. This frequency band excludes the vehicle and bridge resonances and highlights the damage information, which improves the robustness of our approach to vehicle-bridge variability. Damage location and severity are estimated by extracting key peak features such as the peak location, amplitude, energy, width, and slope from the reconstructed signal, and importing them to Gaussian Mixture Model clustering, which provides insights into the outcome labels through probabilistic distribution in an unsupervised fashion [8].

Our approach is evaluated on a numerical VBI simulation, which includes three vehicle types, six bridge lengths, and three bridge cross-sections. The simulation also takes into account variability in vehicle properties, such as vehicle speed, mass, and damping ratio. This study considers various damage scenarios, including two damage locations and three damage severities modeled by stiffness reductions. Our approach achieves a mean absolute percentage error (MAPE) of 0.78% for damage localization and 13.13% for damage quantification across various vehicle and bridge configurations, demonstrating its potential for adaptability to different VBI systems. It is also capable of damage diagnosis with varying vehicle speeds, making it more practical for real-world implementation without the need for a specific speed range.

BRIDGE DAMAGE DIAGNOSIS THROUGH PHYSICS-INFORMED SIGNAL DECOMPOSITION

This section presents our bridge damage diagnosis approach that extracts robust and damage-sensitive features using a physics-informed signal decomposition method. The approach consists of three phases (as outlined in Figure 1), which are described in the following subsections.

Vehicle Vibration Signal Pre-Processing and Time-Frequency Representation

This section describes a two-step pre-processing of the drive-by vehicle vibration signals. In the first step, the vibration signals are normalized by dividing them by their corresponding vehicle velocity. This normalization is conducted to eliminate the effect of the vehicle velocity on the signal amplitude (e.g., the faster the vehicle, the larger the signal amplitude.) Then, a Hanning window function is multiplied with the signal to reduce the amplitude of the discontinuities at the boundaries of each finite sequence (i.e., reduce the spectral leakage).

In the second step, SWT is used to decompose the pre-processed drive-by vehicle vibration signal into the time-frequency domain, which contains the damage-sensitive information of the damage location and severity [9]. Compared to conventional wavelet transform methods, SWT represents the non-stationary drive-by vehicle vibration signal as a superposition of intrinsic mode function components, extracts high-precision time-

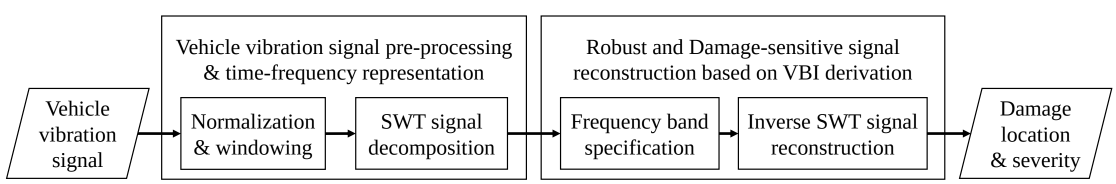


Figure 1. The flowchart of our bridge damage diagnosis approach through physics-informed signal decomposition.

frequency curves through energy reassignment and wavelet coefficient squeezing, and therefore offers a more accurate representation of the signal's time-frequency characteristics [4]. Moreover, SWT has been shown to be more robust to noise, thereby offering enhanced reliability for damage detection in various VBI systems which may be exposed to different environmental conditions [10].

Robust and Damage-Sensitive Signal Reconstruction Based on Physics Derivation of the Vehicle-bridge Interaction System

This section studies the dynamic interaction between a bridge and a moving vehicle to provide physical insights for reconstructing a damage-sensitive signal proportion from the pre-processed drive-by vehicle vibration signal. This signal reconstruction phase reduces the vehicle-bridge variability and highlights the damage-sensitive information by minimizing the effects of vehicle and bridge resonances. Specifically, the bridge and the moving vehicle are considered two elastic structures characterized by distinct vibration frequencies and are coupled together through interaction forces at the contact points. With omitting the damping and assuming the mass of the vehicle is far less than the bridge's, the closed-form solution of the drive-by vehicle vertical acceleration is attained and separated into three terms [4]:

$$\begin{aligned}\ddot{y}(t) = \sum_{n=1}^{\infty} C_{1n}\sin(w_v t) + \sum_{n=1}^{\infty}\big[C_{2n}\phi_n(vt)\sin(\omega_n t) + C_{3n}\dot{\phi}_n(vt)\cos(\omega_n t)\\ + C_{4n}\ddot{\phi}_n(vt)\sin(\omega_n t)\big] + \sum_{n=1}^{\infty} C_{5n}\big[\phi_n(vt)\ddot{\phi}(vt) + \dot{\phi}_n(vt)^2\big]\end{aligned} \tag{1}$$

where C_{1n}, C_{2n}, C_{3n}, C_{4n} and C_{5n} are constants depending on material and geometry properties of the VBI system; $w_n = 2\pi f_n$ is the bridge frequency at the n^{th} mode, $w_v = 2\pi f_v$ is the natural frequency of the vehicle.

The dominant frequency of each term in Eq (1) is vehicle frequency, bridge frequencies, and the instantaneous frequencies of mode shapes, respectively. Specifically, the dominant frequencies of the third term $y_d = \sum_{n=1}^{\infty} C_{5n}\big[\phi_n(vt)\ddot{\phi}(vt) + \dot{\phi}_n(vt)^2\big]$, can be approximated by the driving frequency $w_{d,n} = \frac{n\pi v}{L} = 2\pi f_{d,n}$ for $n = 1, \dots,$ which are not affected by the bridge and vehicle resonances. y_d contains the multiplications of the mode shape derivatives, which amplifies the damage information included in the mode shape functions [4, 6]. Additionally, $C_{5n} = \frac{\omega_v^2\omega_n^2 m_v g}{k_n(\omega_n^2 - \omega_{d,n}^2)}\frac{\omega_{d,(n+1)}^2}{(\omega_v^2 - \omega_{d,(n+1)}^2)}$, where k_n is the bridge stiffness, m_v is the vehicle mass, and g is the gravitational acceleration. C_{5n} is less susceptible to degradation as the number of modes (n) increases, resulting in the higher mode components of y_d having a larger amplitude compared to other terms. Therefore, y_d is both damage-sensitive and robust to vehicle-bridge variability, and it can be specified by selecting an appropriate frequency band that only includes $f_{d,n}$.

To this end, a robust damage-sensitive signal is reconstructed from the decomposed time-frequency SWT components by computing the inverse SWT within a specified frequency band: $\mathbf{f}_s$. This frequency band includes the driving frequencies: $f_{d,n} \in \mathbf{f}_s$, and excludes the bridge and vehicle frequencies: $f_n, f_v \notin \mathbf{f}_s$.

Damage Diagnosis Based on Gaussian Mixture Model Clustering Algorithm

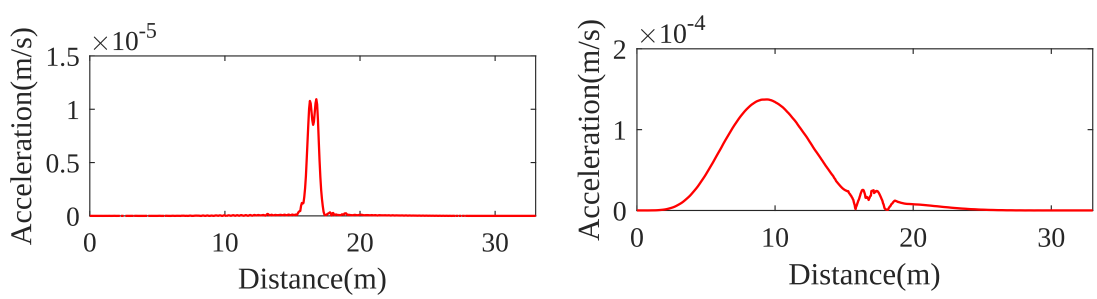
This section presents the third phase of our bridge damage diagnosis approach, which estimates damage location and severity using the Gaussian Mixture Model (GMM) clustering algorithm. Firstly, the peak features of the reconstructed damage-sensitive signal are calculated. These features include the peak location, amplitude, energy, prominence width, and slope. The peak slope is defined as the ratio of the peak prominence height and width. Figure 2 (a) shows an example of the reconstructed damage-sensitive signal interpolated to the spatial domain along the bridge having local damage at the mid-span (i.e., damage at 16.5 m for a 33 m bridge). The damage location is estimated directly using the spatial coordinate of the peak wave.

Furthermore, the peak amplitude is sensitive to both the damage severity level and noise, and therefore, estimating damage severity solely relies on the peak amplitude is not reliable. For instance, Figures 2 show the reconstructed damage-sensitive signals of two drive-by vehicle vibrations due to (a) the damage and (b) the signal noise without damage. It can be observed that both of the two signals have a peak wave. However, the reconstructed signal with bridge damage has a larger ratio between the prominence amplitude and the prominence wide. Consequently, multiple peak features, such as amplitude, energy, prominence width, and slope, are input to a Gaussian Mixture Model (GMM) clustering algorithm for achieving more accurate damage severity quantification. The GMM clustering algorithm is used because it offers probabilistic distributions of damage severity estimations, providing valuable insights even in cases where the cluster boundaries are ambiguous [8]. Additionally, its unsupervised nature minimizes the need for extensive manual data labeling, enhancing its practicality for damage diagnosis.

EVALUATION ON NUMERICAL VBI MODELS

Our approach is evaluated on a numerical VBI simulation introduced in [11]. This section presents the data description and our evaluation results.

Data Description



(a) (b)

Figure 2. Example of reconstructed damage-sensitive signals of two drive-by vehicle vibrations due to (a) the damage at mid-span and (b) the signal noise without damage. Both of the two signals have a peak wave, but their peaks have different features.

The simulated dataset includes various VBI systems, including six bridges with different lengths (9m, 15m, 21m, 27m, 33m, and 39m) and cross-sections (T beam, Y beam, and Super-Y beam), and three vehicle types (one-axial oscillators, two-axial sedans, five-axial trucks). The main body of the vehicle is modeled as a rigid body, while the axles are represented as lumped masses. The body and axles are interconnected using spring and dashpot systems that represent the suspensions. The bridge is modeled as a simply supported beam. The vehicle properties, including body and axle mass, stiffness, and damping of the suspension system, are randomly sampled based on the given statistical variation (i.e. maximum, minimum, and standard deviation). There are six damage scenarios, consisting of three damage severities (undamaged, 20% stiffness reduction of a 0.5-meter beam element, 40% stiffness reduction of a 0.5-meter beam element) and two damage locations (damage at quarter-span or mid-span). For each scenario, 400 events with random vehicle properties are generated, and each event contains the vertical acceleration response from both the wheel and main body with a sampling period of 0.0038 seconds. In total, our dataset consists of $6\ (bridges) \times 3\ (vehicle\ types) \times 2\ (damage\ location) \times 3\ (damage\ severity) \times 400\ (events) = 43,200\ (data\ samples)$. Details of this dataset can be found in [11].

Drive-by vehicle vibration signals from the unsprung wheels are used for damage diagnosis because the wheels are in contact with the bridge, and their vibrations contain more bridge information compared to the sprung body vibrations. Moreover, for two-axial sedans and five-axial trucks, signals from different wheels are shifted in the spatial domain to the same contact location to account for the vehicle wheelbase length. This process allows us to utilize signals from all wheels, which amplifies the extracted damage information.

Results and Discussion

Our approach achieves an overall 0.78% mean absolute percentage error (MAPE) for damage localization and 13.13% MAPE for damage quantification of the six bridges

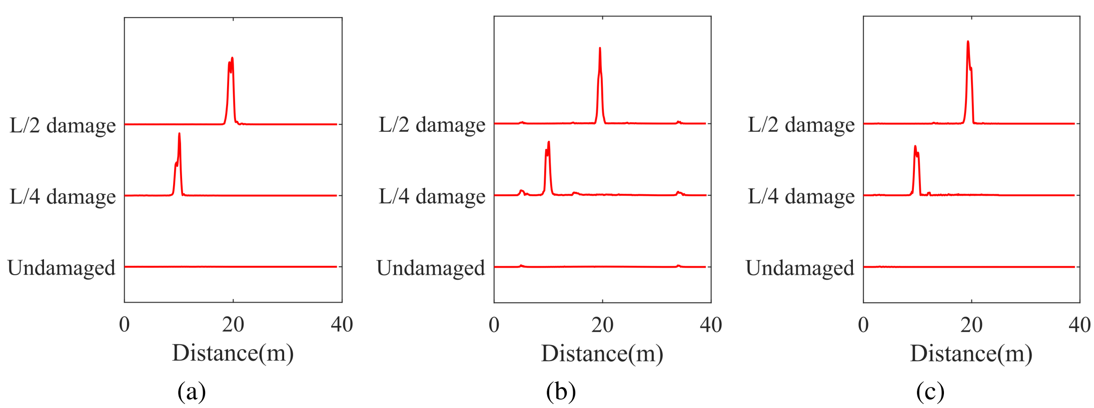


Figure 3. Reconstructed damage-sensitive signals for different damage locations and vehicle configurations, including (a) one-axial oscillators and (b) two-axial sedans, and (c) five-axial trucks. Damage localization results using our approach are robust to different vehicle configurations.

and three vehicle configurations. The damage diagnosis results for different bridge configurations using one-axial oscillators are summarized in Table I. The average MAPE is 0.76% for localization and 14.19% for quantification across bridges of varying lengths and cross sections, demonstrating its scalability and robustness to different bridge systems. The damage location can be indicated by the distance coordinate of the peak wave, as shown in Figure 3. Note that damage localization and quantification results for shorter bridges are less accurate than those for longer bridges. This could be because shorter bridges generally have a higher mode density, meaning that there are more closely spaced natural frequencies compared to longer bridges which may result in more challenging identification and separation of individual modes in the damage-sensitive frequency band selection process.

The damage diagnosis results for different vehicle configurations on bridge B6 (39 m with Super-Y beam) are presented in Table II. An average MAPE of 0.83% in localization and 10.99% in quantification is achieved. The reconstructed vibration signals, as illustrated in Figure 3, showcase a precise and distinct representation of the damage-sensitive peak wave across V1, V2, and V5, demonstrating the approach's robustness in handling different vehicle configurations. For damage quantification, the error is notably lower for two-axle sedans compared to one-axle oscillators. This improvement can be attributed to the utilization of vibration signals from multiple wheels, which provides more damage information. However, the error is relatively larger for five-axle trucks, potentially due to the complexity of the truck's motion, where the truck's vertical vibrations include the rotational components of the tractor and trailer.

TABLE I. DIAGNOSIS RESULTS FOR DIFFERENT BRIDGE CONFIGURATIONS.

	B1	**B2**	**B3**	**B4**	**B5**	**B6**
Bridge length	9m	15m	21m	27m	33m	39m
Bridge cross section	T	T	Y	Y	SY	SY
Damage localization MAPE (%)	0.82	0.78	0.77	0.79	0.76	0.63
Damage quantification MAPE (%)	15.26	14.93	13.96	14.63	13.79	12.62

T: T beam; Y: Y beam; SY: Super-Y beam.

TABLE II. DIAGNOSIS RESULTS FOR DIFFERENT VEHICLE CONFIGURATIONS.

	V1	**V2**	**V5**
Damage localization MAPE (%)	0.63	0.65	1.21
Damage quantification MAPE (%)	12.62	7.11	13.25

V1: one-axial oscillators; V2: two-axial sedans; V5: five-axial trucks.

CONCLUDING REMARKS

In this paper, a robust drive-by BHM approach is introduced to diagnose bridge damage with large vehicle-bridge variability. The synchro-squeezed wavelet transform (SWT) method is used to pre-process the drive-by vehicle vibration signal and represent it in the time-frequency plane. A damage-sensitive signal is reconstructed by computing the inverse SWT within a physics-informed frequency band. This frequency band excludes the vehicle and bridge resonant frequencies to reduce the effects of vehicle-bridge variability and amplifies the damage information in the pre-processed vibration signal. Damage diagnoses are performed using peak features of the reconstructed signal, which are informative to the damage location and severity. Our approach achieves an overall 0.78% MAPE for damage localization and 13.13% MAPE for damage quantification of six bridges and three vehicle configurations.

REFERENCES

1. Li, J., X. Zhu, S. seong Law, and B. Samali. 2019. "Indirect bridge modal parameters identification with one stationary and one moving sensors and stochastic subspace identification," *Journal of Sound and Vibration*, 446:1–21, ISSN 0022-460X, doi:https://doi.org/10.1016/j.jsv.2019.01.024.
2. Yang, Y.-B., C. Lin, and J. Yau. 2004. "Extracting bridge frequencies from the dynamic response of a passing vehicle," *Journal of Sound and Vibration*, 272(3):471–493, ISSN 0022-460X, doi:https://doi.org/10.1016/S0022-460X(03)00378-X.
3. Liu, J., S. Xu, M. Bergés, and H. Y. Noh. 2023. "HierMUD: Hierarchical multi-task unsupervised domain adaptation between bridges for drive-by damage diagnosis," *Structural Health Monitoring*, 22(3):1941–1968, doi:10.1177/14759217221081159.
4. Liu, J., B. Chen, S. Chen, M. E. Berges, J. Bielak, and H. Y. Noh. 2020. "Damage-Sensitive and Domain-Invariant Feature Extraction for Vehicle-Vibration-Based Bridge Health Monitoring," *ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*:3007–3011.
5. Zhu, L. and A. Malekjafarian. 2019. "On the Use of Ensemble Empirical Mode Decomposition for the Identification of Bridge Frequency from the Responses Measured in a Passing Vehicle," *Infrastructures*.
6. Yang, Y., Y. Li, and K. Chang. 2014. "Constructing the mode shapes of a bridge from a passing vehicle: A theoretical study," *SMART STRUCTURES AND SYSTEMS*, 13:797–819, doi:10.12989/sss.2014.13.5.797.
7. Malekjafarian, A., C. Moloney, and F. Golpayegani. 2021. "Drive-by Bridge Health Monitoring Using Multiple Passes and Machine Learning," .
8. Figueiredo, M. and A. Jain. 2002. "Unsupervised learning of finite mixture models," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 24(3):381–396.
9. Liu, J., S. Chen, M. Bergés, J. Bielak, J. H. Garrett, J. Kovačević, and H. Y. Noh. 2020. "Diagnosis algorithms for indirect structural health monitoring of a bridge model via dimensionality reduction," *Mechanical Systems and Signal Processing*, 136:106454.
10. Daubechies, I., J. Lu, and H.-T. Wu. 2011. "Synchrosqueezed wavelet transforms: An empirical mode decomposition-like tool," *Applied and Computational Harmonic Analysis*, 30(2):243–261, ISSN 1063-5203, doi:https://doi.org/10.1016/j.acha.2010.08.002.
11. Sarwar, M. Z. and D. Cantero. 2021. "Deep autoencoder architecture for bridge damage assessment using responses from several vehicles," *Engineering Structures*.