Comparative Evaluation of Robot and Portable SHM Platforms for Drive-By Bridge Modal Identification

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ABSTRACT

Bridge infrastructures lack affordable network-wide monitoring, as fixed S HM is typically limited to landmark spans. Drive-by monitoring with mobile robots offers scalable coverage using vehicles as moving sensor platforms. This paper experimentally evaluates a frequency domain subtraction algorithm on vibration data collected by an unmanned ground vehicle (UGV), validated against a portable SHM system on the UCF footbridge and the Alafaya Trail Bridge. The paired on-bridge and adjacent-road vibrations are transformed by FFT, scaled by energy and subtracted to isolate the dynamic response of the bridge and reveal modal peaks. On the footbridge, the UGV consistently recovered four of eight modal frequencies while on the stiffer Alafaya bridge, it identified the fundamental mode within 0.35% of the reference. Though portable SHM yields higher fidelity, it lacks network f easibility. UGV-based monitoring achieves a practical balance of accuracy and consistency. Future work will address uncertainty quantification, advanced modal frequency extraction algorithm and mode-shape extraction.

Keywords. Drive-by Bridge Monitoring, Structural Health Monitoring, Robotics, Connected Vehicle, Modal Identification.

INTRODUCTION

Civil infrastructure supports mobility, commerce, and public safety, yet a large share of bridges are aging and are increasingly exposed to extreme weather and deterioration [1,2]. Although recent federal spending offers relief, turning investment into measurable gains will still require many years of sustained effort [5,6]. Continuous, network-wide condition data are, therefore, indispensable. Fixed structural health monitoring (SHM) installations provide high-fidelity i nformation, but r emain e conomically f easible only for landmark spans [3].

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Drive-by bridge monitoring meets this need by treating passing vehicles as mobile sensors that record vibrations while crossing a span, providing a wide coverage without permanent hardware on the structure [4, 5]. Numerical and field demonstrations two decades ago confirmed that vehicle accelerations embed bridge modal frequencies [6, 7]. Since then, advances in low-noise accelerometers, connectivity, and edge computing have enabled the deployment of connected vehicles (CVs), smartphones, and unmanned ground vehicles (UGVs), greatly expanding data volume and spatial reach [8–11]. Electric CVs reduce engine noise, while UGVs allow repeatable speed and trajectory control, yielding high-quality datasets.

However, accurate modal identification remains challenging. Road surface roughness injects broadband energy that obscures structural peaks, and vehicle suspensions superimpose their own modes [12–16]. Mitigation strategies, such as large-sample averaging, tapping-scanning rigs, or vehicle-based amplifiers, require heavy data handling or bespoke hardware [17–22]. Conventional bandpass filtering suppresses vehicle signatures but requires detailed knowledge of the dynamics of each vehicle [23, 24]. Reconstruction of the contact point response theoretically eliminates the influence of the vehicle but depends on suspension parameters that are rarely available in fleet settings [25–27].

This study tackles these limitations with a vehicle-independent frequency-domain subtraction technique that pairs measurements on the bridge and adjacent road, rescales their spectra, and subtracts them to isolate the response of the bridge. By clarifying hidden peaks, the method enables reliable modal identification under routine traffic and moves drive-by monitoring closer to true network-level deployment.

BRIDGE MODE IDENTIFICATION METHODOLOGY

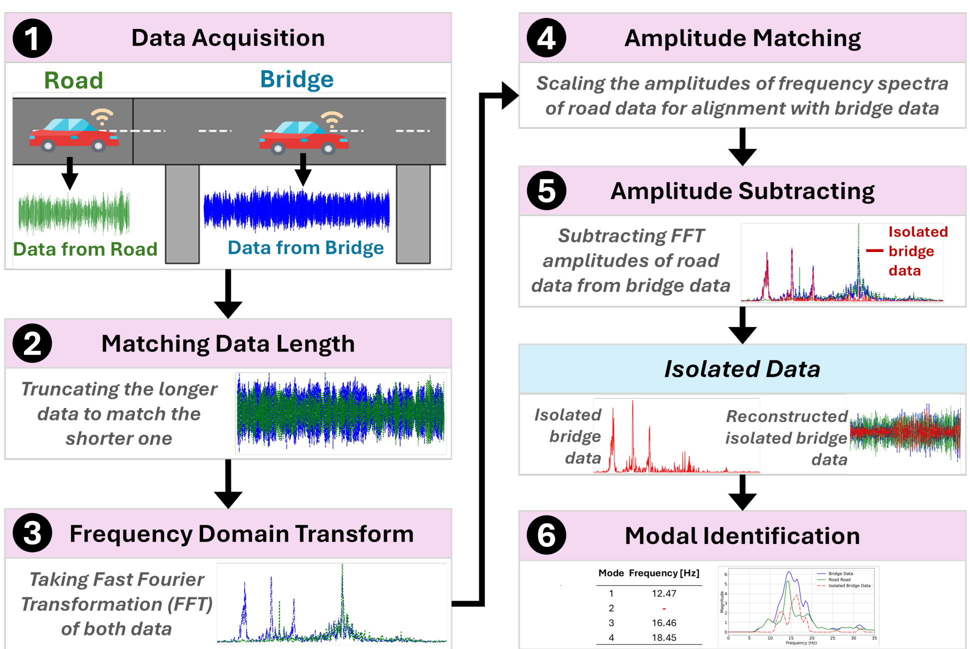


Figure 1. Used methodology for identifying bridge vibration modal frequencies.

The proposed method takes advantage of the vehicle passing on the adjacent roadway to record a baseline vibration spectrum, then isolates the dynamic response of the bridge by subtracting this baseline from the combined bridge-vehicle spectrum. Under linear superposition assumption, the on-bridge measurement is denoted as:

$$H_B(f) = H_b(f) + H_r(f) + H_v(f) + H_s(f) + H_n(f), \tag{1}$$

where H_b, H_r, H_v, H_s, and H_n denote the response of the bridge, the road profile, the dynamics of the vehicle, the effects of speed and noise, respectively. While the roadway spectrum is defined as:

$$H_R(f) = H_r(f) + H_v(f) + H_s(f) + H_n(f) \tag{2}$$

Assuming constant speed and similar surface materials, subtracting a suitably scaled H_R from H_B yields the isolated bridge term $H_b(f)$. Both time-series recordings are first mean-removed and truncated or padded to equal length N. Fast Fourier transforms then produce amplitude spectra $|H_B(f)|$ and $|H_R(f)|$, from which we compute the energy-based scaling factor as:

$$\text{SF} = \frac{\sum_{k=0}^{N/2} |H_B(f)|}{\sum_{k=0}^{N/2} |H_R(f)|} \tag{3}$$

Then we can form the new scaled spectrum response of the roadway as:

$$|H_{R,\text{scal}}(f)| = \text{SF}\, |H_R(f)|. \tag{4}$$

Amplitude subtraction then follows:

$$|H_b(f)| = |H_B(f)| - |H_{R,\text{scal}}(f)|. \tag{5}$$

A Hamming window and Gaussian smoothing are applied to $|H_b(f)|$ to reduce spectral leakage and suppress high-frequency noise. Finally, the power spectral density of $|H_b(f)|$ highlights the dominant peaks, which are manually identified as the bridge's natural frequencies. Future work will extend this framework to automated mode-shape extraction under real traffic conditions.

TEST STRUCTURES AND EXPERIMENTATION SETUP

The experiments were carried out on two in-service bridges, the UCF Footbridge and the Alafaya Trail Bridge (Figures 2–3a)—using a bespoke unmanned ground vehicle (UGV) named 'Cypector'. Built on Clearpath Robotics' Husky A200 chassis by UCF's Civil Infrastructure Technologies for Resilience and Safety (CITRS) lab. Cypector is equipped with two Velodyne VLP-16 LiDAR units, a Garmin GPS-18x receiver, an ADK infrared camera, dual FLIR Blackfly S industrial cameras, a Stereolab ZED 2 stereo camera, an Occam Omni 60 panoramic camera, a Microstrain 3DM-GX5-25 IMU, a GPU-accelerated Mini-ITX computer, and a gigabit wireless router. These sensors enable simultaneous capture of vehicle dynamics and environmental context during each drive-by pass.

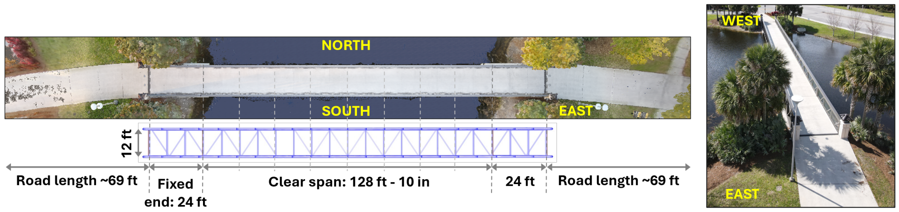
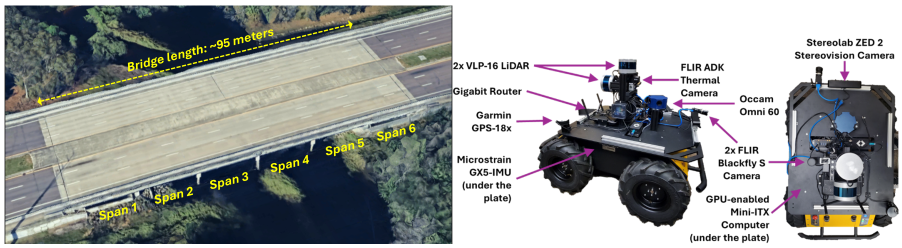


Figure 2. UCF Footbridge bridge.



(a) Alafaya Trail Bridge.

(b) Cypector UGB.

Figure 3. Alafaya trail bridge and the UGV used for data collection.

To benchmark the subtraction methodology, we used a portable structural health monitoring (SHM) system comprising ultra-sensitive S-Lynk wireless accelerometer nodes alongside the Microstrain IMU (Table I). The S-Lynk units provide a measurement range $5m/s$ with 24-bit resolution and a noise density below 30 $ng/\sqrt{Hz}$, ensuring accurate recording of low-frequency bridge responses, an area where conventional MEMS devices often fall short.

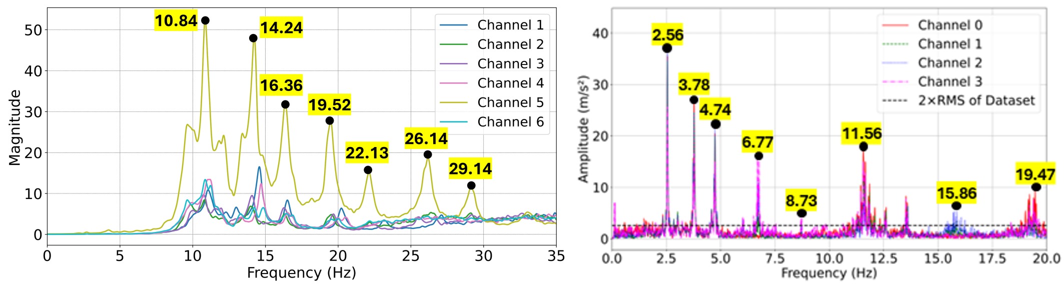
TABLE I. Datasheet of the accelerometer sensors used in the experiment.

Sensor	Measurement Range	Resolution	Noise Density
Sercel S-Lynks	$\pm 5\ m/s^2$	24-bits digital output	$<$ 30 $ng/\sqrt{Hz}$
Microstrain 3DM-GX5-25	40g	0.02 mg	2 $\mu g\sqrt{Hz}$

RESULTS AND DISCUSSION

This section presents the bridge modal frequency identification results of the drive-by tests (footbridge and Alafaya Trail Bridge) and comparatively analyzes them with the results obtained from the portable SHM system. For this, first, the frequencies are identified using the monitoring dataset from the portable SHM system, forming the reference dataset, as shown in Figure 4. The frequencies are then identified from the robot drive-by data and subsequently compared to the reference dataset obtained from the portable SHM system, as shown in Figure 5 and Tables II-III.Results show that subtracting the road from the bridge effectively cancels out amplitudes in certain frequency ranges while some large and small peaks remain in others, generally indicating the presence of bridge vibration modes. The most apparent peaks after these subtractions are selected as the bridge modes.

As shown in Figure 4, the first eight modal frequencies of the footbridge were successfully identified under normal operational conditions. On the other hand, seven modes were identified using the portable system on the Alafaya Trail bridge.

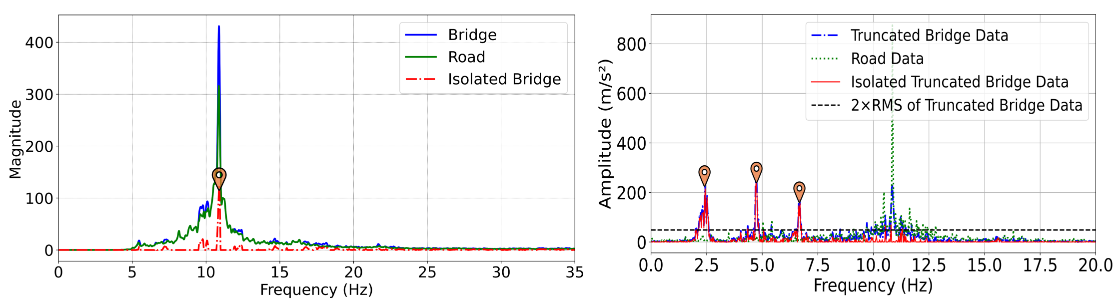


(a) Alafaya Trail Bridge.

(b) UCF footbridge.

Figure 4. Identified modal frequencies using the portable SHM.

As shown in Figure 5, showing the frequency domain of road, bridge and isolated bridge data. We can notice that on the footbridge results Figure 5b we can see a considerable decrease in the amplitude of the isolated bridge signal, indicating that the robot's mode is around 11Hz. Three modes out of 8 were identified in the sample run shown, which was similar to the three conducted runs. However, the difference from the reference results has not exceeded 1%. On the other hand, the extracted modes did not perform as well on the Alafaya trail, with only one identified modes out of the seven modes which was also consistent on all conducted runs (Figure 5a. We can also notice, that the detected mode is around 11Hz, which is close to the Robot's frequency. Using the proposed methodology we managed to detect the bridge mode even while it is masked by the robot frequency.



(a) Alafaya Trail Bridge.

(b) UCF footbridge.

Figure 5. Identified modal frequencies with robot Drive-by in one run.

Tables II-III summarize the results from all runs on each bridge with the difference from the reference dataset. In general the variability in the detection is below 3% which can be considered a decent performance. One constraint of the proposed methodology lies in its assumption that subtracting the road response from the bridge will perfectly isolate the bridge's dynamic signature. Finally, we speculate that the presence of residuals in the frequency domain amplitude suggests several possible contributing factors: (1) Surface inconsistencies between the bridge and roadway, caused by inherent material and construction heterogeneity; (2) While the methodology assumes linear superposition as in Equations 1-2, real-world vehicle-bridge interactions could involve non-linear and higher-order harmonics that are not fully captured through simple subtraction.

TABLE II. Identified modal frequencies of all robot runs on the footbridge.

Mode	Frequency [Hz] - Reference	Frequency [Hz] - Robot	Difference [%]
1	2.56	2.50	2.47%
2	3.78	-	-
3	4.74	4.69	1.05%
4	6.77	6.67	1.53%
5	8.73	8.92	2.18%
6	11.56	-	-
7	15.86	-	-
8	19.47	-	-

TABLE III. Identified modal frequencies of all robot runs on the Alafaya Trail bridge.

Mode	Frequency [Hz] - Reference	Frequency [Hz] - Robot	Difference [%]
1	10.84	10.88	0.35%
2	14.24	-	-
3	16.36	-	-
4	19.52	-	-
5	22.13	-	-
6	26.14	-	-
7	29.14	-	-

CONCLUDING REMARKS

The proposed subtraction-based drive-by monitoring method offers a practical means of extracting bridge modal frequencies under real traffic, yet it rests on key assumptions that may limit its generality. In particular, it assumes consistent vehicle speed and comparable pavement properties before and during the crossing. Although maintaining a steady speed is easily achievable in controlled experiments or guided automated vehicles, matching the surface characteristics of the approach roadway and bridge deck remains challenging, as the first is often asphalt and the latter concrete.

Experimental results in two distinct bridges further illustrate both the promise and the constraints of this approach. On the UCF footbridge, four of the eight analytical modes were reliably identified across three runs, whereas only one of the seven modes emerged clearly on the stiffer Alafaya Trail Bridge. This decreased performance may reflect the higher deck stiffness, the limited speed range of the UGV, or the fact that the data were collected from a sidewalk lane rather than the roadway itself. In particular, the robot's own structural resonance at approximately 11 Hz overlapped the Alafaya bridge's first mode; despite this masking, the subtraction technique recovered the fundamental frequency with just 0.35% error. Residual discrepancies in the isolated spectra appear to be due to the differing surface materials on the road and bridge.

In the future, validating the methodology with commercial vehicles will be essential to demonstrate scalability beyond robotic platforms. Future work will also quantify the uncertainty associated with different vehicle types and develop enhanced analysis routines that incorporate uncertainty and improve generalization across bridge classes. Finally, extending the framework to recover not only modal frequencies, but also mode shapes will further strengthen drive-by monitoring as a comprehensive tool for network-level bridge assessment.

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