Life-Cycle Performance of Structures and Infrastructure Systems in Diverse Environments – Li & Frangopol (Eds)

Drive-by monitoring using adjacent road information to estimate bridge dynamics

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ABSTRACT: Drive-by/indirect monitoring of bridges demonstrated high practicality for their assessment and evaluation. In this study a drive-by monitoring methodology using a four-wheeled robot equipped with multi-modal sensors is developed. The method isolates the bridge vibration response from other factors like road roughness and vehicle dynamics by leveraging data from adjacent roadways. The methodology also explores the effect of varying the robot's trajectory on different sides over the bridge to determine optimal conditions for precise real-time mode identification. Experiments on a real-world bridge demonstrated the identification of up to four modes, with an average variation of 2% compared to reference monitoring data. Driving trajectories showed minimal impact on results, suggesting comprehensive identification.

Keywords: Drive-by Bridge Monitoring, Structural Health Monitoring, Robotics, Modal Identification, Structural Reliability

1 INTRODUCTION

Recent advancements in bridge monitoring have leveraged technology-driven strategies (Luleci et al. 2024). Vehicle-derived data emerged as a key approach, first proposed by Yang et al. (2004) through numerical simulations of a spring-mass vehicle model interacting with a simply supported beam to determine bridge frequency. Lin et al. (2005) validated this concept through field testing on Taiwan's Da-Wu-Lun Bridge using a tractor-trailer system. Subsequent studies refined the methodology for bridge condition assessment (Bu et al. 2006; Hester et al. 2015; Kim et al. 2008), establishing vehicles as mobile sensors and inspiring further research. Over the past two decades, studies have explored extracting bridge information from vehicle responses via the VBI process, using simulations, lab experiments, and limited field tests (Malekjafarian et al. 2022; Singh et al. 2023; Xu et al. 2024). Identifying bridge frequencies from vehicle accelerations underpins applications like damage detection and residual life prediction (Corbally et al. 2021a; Li et al. 2023). Since 2004, research has examined vehicle parameters, signal processing methods, and custom-engineered vehicles for indirect bridge frequency identification (Jin et al. 2022; Li et al. 2022; Obrien et al. 2017; Yang et al. 2009; Yang et al. 2022). Key challenges include interference from road roughness and vehicle dynamics, addressed through tapping scanning and vehicle amplifiers (Hu et al. 2024; Jian et al. 2020; Kong et al. 2016; Xu et al. 2023). Filters have been used to remove vehicle frequencies, but this requires prior knowledge of vehicle specifications (Shirzad-Ghaleroudkhani et al. 2020; Yang et al. 2013). Contact Point (CP) responses were introduced to mitigate these issues, isolating bridge oscillations from vehicle influence (Yang et al. 2018; Li et al. 2023; Liu et al. 2023; Singh et al. 2023). However, CP response extraction often demands precise

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vehicle parameter measurements (Corbally et al. 2021b; Feng et al. 2023), limiting practical application. A novel, pragmatic method is urgently needed for rapid bridge modal parameter estimation and efficient evaluation. Advancements in mobile bridge monitoring enable real-time assessment and cost-effective scalability (Aktan et al. 2000; Gokce et al. 2013). This study experimentally verifies a robot-based indirect monitoring method on an operational bridge. A four-wheeled Unmanned Ground Vehicle (UGV) equipped with multi-modal sensors collects and analyzes bridge response data in near real-time, ensuring accurate measurements as it crosses the structure.

The goal of this study is as follows: Investigating and experimentally validating a practical and scalable methodology for indirect bridge monitoring on a real-world operational bridge using a mobile robot equipped with multi-modal sensors. The study also aims to explore the impact of the robot's trajectory on different sides of the bridge to determine the optimal conditions for precise bridge mode identification. The study scope is limited to several factors: (1) A pedestrian bridge and a short length of connecting roads are used as a test environment; (2) A practical and scalable drive-by monitoring solution without vehicle parameters is investigated; (3) Mode identification is limited to bridge natural frequency identification; (4) Driving on different trajectories on the bridge is limited to three paths covering the bridge width; and (5) No structural damage scenario is considered. The methodology was tested under more diverse speed scenarios in the authors' earlier tests, including fast speed in addition to slow (as in the study herein) and drive-stop while collecting visual data (e.g., LiDAR and image/video) from the UGV. The readers are referred to that study for further information (Luleci, Algadi, et al. 2025).

2 METHODOLOGY

A bridge's vibration modes can be identified by leveraging knowledge from nearby roads to isolate the bridge response data by subtracting the road data from the total data collected over the road. The methodology relies on consistent driving conditions and road surfaces. In a controlled, real-world environment, asphalt and concrete frequency estimation were comparable. Therefore, Figure 1 shows the methodology as follows: Collect data from the roadway and bridge; (2) Match data lengths if needed to ensure frequency domain analysis compatibility; (3) Transform both signals to the frequency domain using Fast Fourier Transformation (FFT); (4) Scale the frequency spectra amplitudes to align them; (5) Subtract the road data's frequency spectrum amplitude from the bridge data to isolate the bridge's frequency domain response; (6) Bridge mode identification using the isolated bridge data. Road surface roughness, vehicle characteristics, driving speeds, and noises can affect vehicle vibration data over a bridge. We isolate the bridge response from these external influences by subtracting the road data from the total data over the bridge to identify modes in the frequency domain. Complex signals can be decomposed into their frequency domains to identify bridge structure natural frequencies. Equation 1 shows the frequency domain signal from a bridge-driving vehicle:

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

where $H_b(f)$ = the bridge response in the frequency domain; $H_r(f)$ = the road response; $H_v(f)$ = the vehicle dynamics; $H_s(f)$ = the driving speeds; and $H_n(f)$ = the noise. Each component's frequency response, denoted as $H(f)$, describes how it reacts across different frequency ranges, which captures the amplitude and phase of the signal as functions of frequency. Similarly, when data is collected by a vehicle driving over an adjacent road connecting bridge, the measured signal from the road in the frequency domain, denoted as $H_R(f)$, contains the same components except for the $H_b(f)$, is represented in Equation 2:

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

The representations (Eq. 1-2) assume linear superimposition, treating the measured signal as the sum of individual components. It also assumes identical vehicle speeds on both roads and bridges for the methodology to work. The frequency domain changes when speeds vary, causing data shifts. The impact of changing road and bridge surface materials on data needs further examination. The study assumes identical road and bridge surface materials for this methodology to work in the test environment.

The data collection process involves collecting vibration data from a vehicle as it traverses the road before and over a bridge. It is crucial to have equal lengths of data from both roads

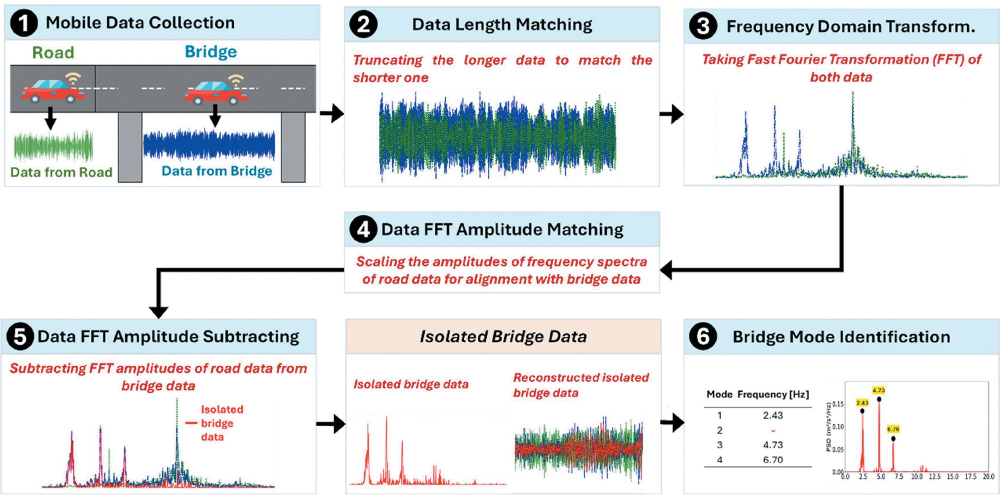


Figure 1. Methodology to identify the bridge vibration modes.

for accurate frequency domain operations. The methodology can consider data from both roads or only from the road after exiting the bridge. If not, the longer data source is truncated to match the shorter one. The mean removal process is implemented for all collected data. For simple data length matching, the bridge data was truncated from both ends of the signal to preserve the semantically richest part. We compared the frequency domains of truncated and untruncated data to ensure they contained the same bridge information. Real-world truncation requires supervision or controlled automation, but not in real-time. Finally, generative artificial intelligence models (Luleci et al. 2023a) could extend the shorter signal with less data loss. The data from the bridge and road is transformed into their frequency domains using the Fourier transform (FFT), with the amplitudes of the truncated data matched by scaling the road's amplitudes to avoid discrepancies in the FFT amplitude range. The amplitude spectra for both signals are calculated as the magnitudes of the FFT results using Equation 3:

$$|H(f)| = \sqrt{Re(H(f))^2 + Im(H(f))^2} \tag{3}$$

where $|H(f)|$ = the amplitude spectra of the data computed (bridge or road); and $Re(\cdot)$ and $Im(\cdot)$ are the reel and imaginary parts of the frequency responses, respectively. Then, the scaling factor is determined by the ratio of the total energy (sum of amplitudes) across all frequency components using Equation 4:

$$Scaling\ Factor = \frac{\sum_{k=0}^{N/2} \left|H_{B,trunc}(f)\right|}{\sum_{k=0}^{N/2} |H_R(f)|} \tag{4}$$

where N = the total number of samples in the signals and $\left|H_{B,trunc}(f)\right|$ is the amplitude spectra of the truncated data collected from the bridge ($N/2$ because of including positive values only). Then, the amplitude spectrum of the data collected from the road $|H_R(f)|$ is scaled using the computed scaling factor as in Equation 5:0

$$\left|H_{R,\,scal}(f)\right| = Scaling\ Factor \cdot |H_R(f)| \tag{5}$$

where $\left|H_{R,\,scal}(f)\right|$ = the amplitude spectrum of the data (collected from the road) after scaling. The isolated bridge response frequency spectrum $H_b(f)$ is used to identify vibration modes using the Power Spectral Density (PSD) calculation. This process normalizes the magnitude of the spectrum by frequency bandwidth, representing the power per unit frequency. This ensures accurate distribution of signal energy across frequency ranges, regardless of data length or sampling rate. PSD is chosen to identify vibration modes as it highlights dominant frequencies more effectively, even in noise or weaker signals. Normalization provides a clearer view of the energy associated with each frequency. Furthermore, the study used the Root Mean Square (RMS) of the PSD as a statistical baseline to identify the bridge's vibration modes. RMS represents the square root of the average power of the signal and is directly related to the signal's standard deviation. The threshold for identifying peaks was $2 \times RMS$ (or 2σ), which captures approximately 95.4% of the energy within the signal, minimizing false positives and guiding to relevant vibration modes. The choice of using 2σ instead of 3σ reflects a balance between sensitivity and specificity, as it captures 99.7%, which would be more restrictive. Both thresholds were tested and found to be effective in guiding the mode identification process. Overall, this threshold guides the selection of peaks to consider during the mode identification process.

3 EQUIPMENT AND EXPERIMENT SETUP

This study tested a four-wheeled UGV called Cypector. More information about the UGC can be found in an earlier study (Luleci et al. 2024).

The experimentation setups were designed to evaluate the methodology and identify bridge vibration modes. A portable SHM system with PCB accelerometers was used as a reference to capture bending and torsional modes, which make up most of the test bridge's structural modes. The drive-by test was conducted in three separate runs, with the robot traversing different sides of

Table 1. Experimentation scenarios (*J* and *S* denote jumping and stop, respectively, while the numbers *.4* and *1* represent the drive speed of the robot).

Test Code	Equipment	Robot Run	Robot Drive Status	Equipment Detail
Reference	Portable SHM system	-	-	NI cDAQ-9178 chassis with NI 9234 module and PCB M603C01 accelerometers
J.4	Mobile Robot	1 2 3	0.4 m/s	UGV equipped with multi-modal sensors (IMU's, Microstrain 3DM-GX5-25, accelerometer is used for data collection)

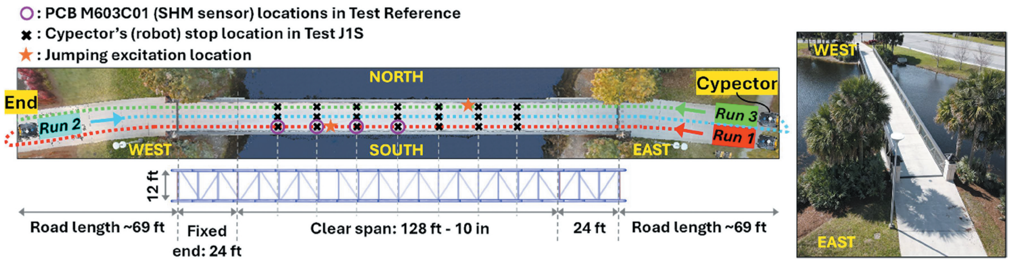
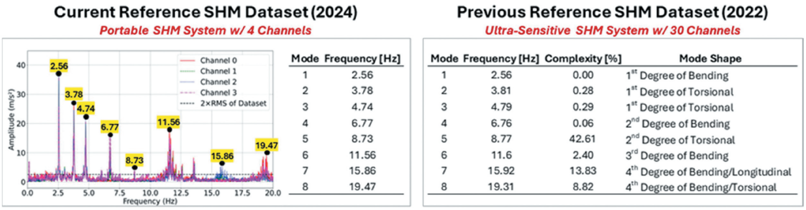


Figure 2. Illustration of the bridge test setups.

the bridge to assess if driving on different sides influenced mode identification outcomes. Table 1 and Figure 2 provide a summary of the experimentation scenarios and sensor configurations.

4 RESULTS AND DISCUSSION

This section compares mode identification results from the reference SHM dataset (2024) to Figure 3's 2022 dataset. The current reference dataset found eight vibration modes with frequency variations of up to 1% from the previous dataset. These variations may be caused by unknown structural changes, weather, or testing errors. Despite these discrepancies, the current reference dataset mode identification results are reliable and serve as a robust baseline for robot-based drive-by monitoring. The peak between 12.5 Hz and 15 Hz in the current test is new or absent from the past test. Identifying this peak requires further investigation. The experiment primarily identifies mode frequencies, not mode shapes.



Mode	Frequency [Hz]
1	2.56
2	3.78
3	4.74
4	6.77
5	8.73
6	11.56
7	15.86
8	19.47

Mode	Frequency [Hz]	Complexity [%]	Mode Shape
1	2.56	0.00	1st Degree of Bending
2	3.81	0.28	1st Degree of Torsional
3	4.79	0.29	1st Degree of Torsional
4	6.76	0.06	2nd Degree of Bending
5	8.77	42.61	2nd Degree of Torsional
6	11.6	2.40	3rd Degree of Bending
7	15.92	13.83	4th Degree of Bending/Longitudinal
8	19.31	8.82	4th Degree of Bending/Torsional

Figure 3. Vibration modes of the test bridge: Current reference dataset (2024) and legacy reference dataset (2022).

Figure 4 shows the bridge and road data in both the time and frequency domains, along with the reconstructed isolated bridge data in the time domain, specifically for Run 1 of J.4. Additionally, one individual jumping on the west side of the bridge exhibited greater jumping intensity compared to the person on the east side, resulting in higher peaks on the west side, as reflected in the data. Moreover, the figure illustrates that when the robot drives at a slow speed, a few dominant peaks around 11 Hz are observed.

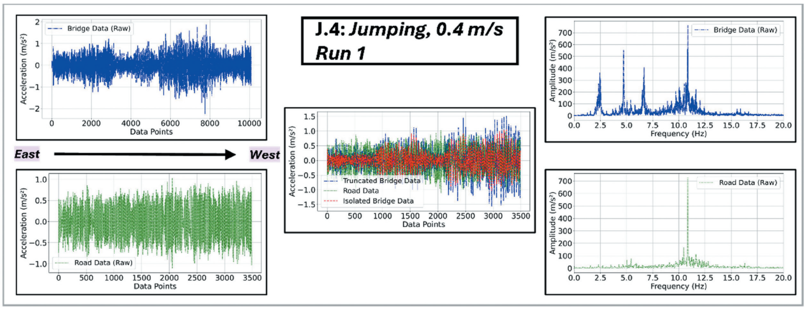
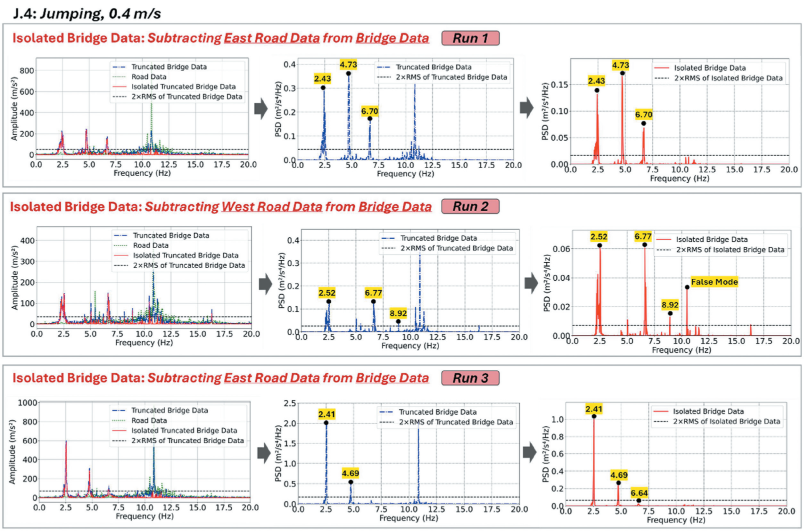


Figure 4. Some of the bridge and road data in the time and frequency domains.

Next, the robot-based indirect monitoring test J.4 results are presented in Figure 5, which shows the mode identification results for three different runs on different bridge sides. The first plot presents the frequency domain (FFT) visualization of truncated bridge data, road data, and isolated bridge data. The second plot shows the frequency domain visualization of only the truncated bridge data, where the bridge modes were identified. The third plot shows the PSD of the isolated bridge data along with the identified modes. The modes identified from the isolated bridge data and their differences from the reference test dataset (2024) are listed in the table below the plot. It is shown that the test identified the first four bridge modes with a variation of up to 5% compared to the reference test, with an average variation of 2%. The robot captured at least three modes per run, with an average mode identification error rate of 2%.

Furthermore, the study found that driving on the sides or middle of a bridge did not significantly impact mode identification results. While it was expected that driving along the middle would capture bending modes and torsional modes, the results were more nuanced. The first torsional mode was missing in Run 2, while the first torsional and bending modes were identified in all Runs 1 and 3. The results may vary based on the bridge type, as the flexibility and geometry of the bridge can influence mode capture. For instance, stiffer bridges with localized vibrations require a robot's trajectory to detect certain modes, while more flexible bridges have uniformly distributed modes. Therefore, conducting runs along all sides of the bridge is recommended for comprehensive mode identification. When the robot is at a slow speed (0.4 m/s), there are a few irregular peaks around 11 Hz in the frequency domain of the road data. This irregularity is caused by road data $H_R(f)$, which contains information about the robot's dynamics, driving speed, and noises (Equation 2). As seen in the figures, the paper's methodology, overall, works satisfactorily in subtracting road data $H_R(f)$ from $H_B(f)$, hence discarding all other involved interfering components (e.g., vehicle, speed, noises) and isolating the bridge data $H_b(f)$. Without the isolation methodology, identifying modes can be significantly challenging due to the involved irregularities in the frequency domain, and this could lead to potentially selecting false modes like those noted in run 2.



Mode	Frequency [Hz]	Difference from Reference (2024)
1	2.43	5%
2	-	-
3	4.73	0%
4	6.70	1%

Run 1

Mode	Frequency [Hz]	Difference from Reference (2024)
1	2.52	2%
2	-	-
3	-	-
4	6.77	0%
5	8.92	2%

Run 2

Mode	Frequency [Hz]	Difference from Reference (2024)
1	2.42	5%
2	-	-
3	4.69	1%
4	6.64	2%

Run 3

Figure 5. Test J.4 results: Drive-by mode identification results for three runs when the robot is at a slow speed and the bridge is under jumping excitation.

The study found minor residuals after applying the isolation methodology, which should have left only the bridge response data. Four possible factors contributed to these residuals: (1) the road surface's heterogeneity, (2) the omission of dynamic interactions between vehicle-road and vehicle-bridge due to coupling effects, and (3) the unaccounted influence of non-linear interactions, such as dynamic dependencies and higher-order harmonics in the assumption of superimposition. These factors could have caused residuals when road data was subtracted from bridge data. Future work should focus on refining the paper's methodology to isolate the bridge response from other factors while accounting for non-linear interactions and dynamic dependencies. Utilizing data from adjacent roads can be effective in isolation while collecting large sets of data can provide better statistical characterization. Advanced signal processing techniques, such as variational mode decomposition (OBrien et al., 2017) and deep learning methods (Luleci et al. 2022, 2023b), can enhance the ability to capture and address non-linear influences. Experimental validation through controlled and real-world tests encompassing different bridge types, surface types, vehicle speeds, and excitation levels will provide critical insights, fostering further optimization and improving the robustness of this methodology.

5 CONCLUSIONS AND RECOMMENDATIONS

A mobile robot with multi-modal sensors was used for scalable indirect bridge monitoring. Data from adjacent roadways helped isolate bridge responses from road roughness and vehicle dynamics. Various robot trajectories were tested for mode detection, and vibration modes were analyzed under limited scenarios. The study's main findings are:

- The proposed methodology effectively isolates bridge vibration modes by mitigating road roughness, vehicle dynamics, and external factors. The robot identified the first four bridge modes with an average variation of 2% from the reference test.
- Mode identification remained consistent across side and middle runs, though the first torsional mode was missing in middle runs. Both torsional and bending modes appeared equally on the south and north sides, with variations depending on bridge flexibility and geometry.
- Residuals after isolation highlight road surface heterogeneity, vehicle interactions, and non-linear dynamics, which the methodology does not fully address. Future refinements should enhance signal processing and account for non-linear effects, validated through real-world testing.
- Future work will refine response isolation by addressing non-linear interactions and using adjacent road data.

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