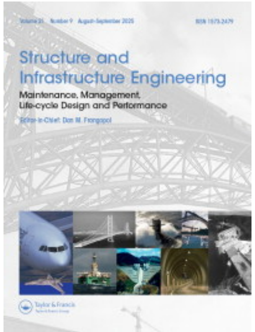

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Robot-based bridge indirect monitoring leveraging road data filtering for modal frequency estimation

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ABSTRACT

Developments in indirect monitoring of bridges demonstrated practical solutions for network-level life-cycle bridge assessment and evaluation. Utilizing mobile robots is a new area for indirect monitoring, offering scalable approaches to data collection and assessment. This study investigates and experimentally validates a drive-by monitoring methodology using a four-wheeled robot equipped with a sensing system. The methodology employs a simple yet practical and effective approach to isolate the bridge vibration response from interfering factors (road roughness, vehicle dynamics, noise) by applying frequency-domain filtering using data collected from the adjacent roadway. Using the methodology, the study explores the effect of varying driving speeds, drive-stop scenarios, and the robot's trajectory on different sides over the bridge to determine optimal conditions for precise bridge mode (frequency) identification. Nine experiments conducted on a real-world bridge under jumping excitation demonstrate the identification of up to six modes, with an average variation of 2% compared to reference monitoring data. Driving trajectories showed minimal impact on results, though runs on all sides suggest comprehensive identification. Robot's dual-capability for real-time mode identification and visual analysis is a promising approach for local assessments in bridge networks, complementing large-scale monitoring by Connected Vehicles in a multi-tiered reliability framework.

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Drive-by bridge vibration monitoring; mobile robot Sensing; modal frequency identification; structural health monitoring; structural reliability

1. Life-Cycle Civil Engineering, and role of SIE journal and Prof. Dan Frangopol's contributions

Over the past two decades, Life-Cycle Civil Engineering (LCCE) has advanced significantly, focusing on the entire lifespan of structures, from planning and design to construction, operation, monitoring, maintenance, rehabilitation, and eventual decommissioning. The LCCE aims to ensure structural safety while optimizing performance, cost, and sustainability. The Structure and Infrastructure Engineering (SIE) Journal, celebrating its 20th anniversary, has played a central role in disseminating research on these topics, a testament to the vision of its founding editor-in-chief, Prof. Dan Frangopol. He has profoundly shaped life-cycle engineering, advancing scientific knowledge and practical applications in structural reliability (Xin et al., 2021), life-cycle performance (Akiyama et al., 2020; Yang & Frangopol, 2019), disaster resilience (Bocchini et al., 2014; Bocchini & Frangopol, 2012), and bridge engineering (Akgül & Frangopol, 2004). As the Founding President of IABMAS (International Association for Bridge Maintenance and Safety) and IALCCE (International Association for Life-Cycle Civil Engineering), he has fostered global collaboration in infrastructure resilience and management. His mentorship has also shaped many researchers, including the senior author of this paper, with collaborations in long-span bridge monitoring (Catbas et al., 2008), system reliability and load rating of movable bridges (Catbas et al., 2011; Gokce et al., 2011), condition assessment of heavy movable structures (Catbas et al., 2014; Gokce et al., 2013), and network-level resilience (Mitoulis et al., 2022). It is an honor to contribute to this special issue celebrating SIE's 20th anniversary and Dr. Frangopol's transformative legacy in engineering. His contributions to infrastructure safety and management have inspired researchers and practitioners to develop novel solutions for resilient and sustainable systems.

One of his seminal works integrates time-dependent structural reliability prediction, highway network performance assessment, and life-cycle cost analysis, optimizing maintenance resources by balancing maintenance, bridge failure, and costs (Liu & Frangopol, 2006). More recently, his review of resilience in infrastructure systems, particularly bridges and transportation networks, has provided frameworks for informed decision-making in resource allocation at the network level (Capacci et al., 2022). Figure 1 illustrates a resilience assessment framework for bridge networks, highlighting the benefits of data-driven vulnerability analysis.

It is also indicated that in most of the research works that tackled the problem of quantifying resilience to support maintenance and management programs of aging and deteriorating structures; the main focus was mainly associated

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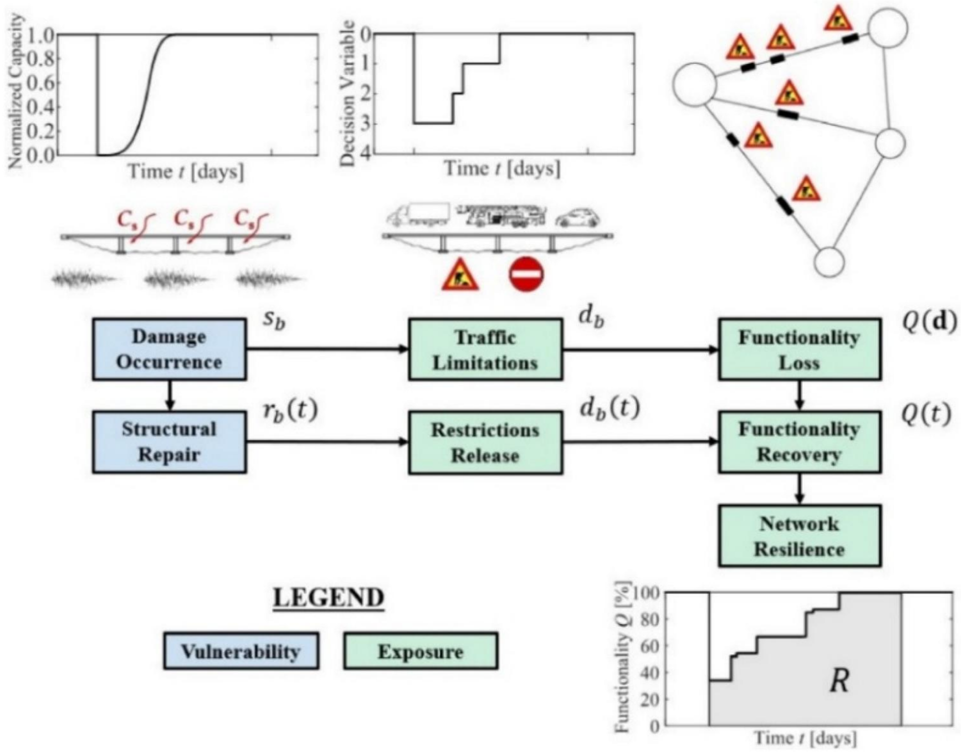


Figure 1. Flowchart for resilience assessment of road networks with vulnerable bridges (Capacci et al., 2022). Note that the network operation and functionality depend on multiple bridges and their performance, which can be determined by analysis, monitoring data, or a combination.

with planning optimal retrofit strategies to reduce the risk of network inoperability due to the failure of existing vulnerable assets (Capacci et al., 2022). One of the critical aspects of optimal decision-making at the network level is to have objective data, desirably data obtained from Structural Health Monitoring (SHM) systems of the bridges in the network. However, this can be challenging and is not a feasible solution as it would require sensors, a dedicated data acquisition system, and permanent installation on bridges and other infrastructures. The advances in mobile sensing technologies, particularly the emerging research domain of vehicle/robot-based drive-by monitoring for identifying the bridge operational dynamics and structural condition assessment, offer new opportunities for monitoring and assessing bridge infrastructures in a more practical and efficient means.

In light of the discussion above, this study presents an experimental investigation into an emerging area of drive-by bridge monitoring using a mobile robot equipped with multi-modal sensors under various driving scenarios, notably, only the onboard accelerometer (part of the Inertial Measurement Unit) was utilized for drive-by monitoring in this study. The study contributes to bridge health monitoring and reliability through multiple key advancements, as listed below:

1. The study introduces a methodology to isolate bridge response from drive-by data by mitigating the effects of road roughness, vehicle-induced dynamics, and other contributory noise through frequency-domain filtering of the bridge data using road data as a reference. This filtering-based approach enhances mode identification by: (i) making true bridge mode peaks more distinct and reducing the likelihood of missing subtler frequencies, (ii) eliminating false mode peaks observed in the raw data, and (iii) enabling the detection of additional bridge modes previously undetectable. However, minor residual effects remain after filtering, with further refinement approaches proposed in Section 8 to improve bridge response isolation.
2. The study establishes an optimal drive-by monitoring strategy for bridge mode identification. By systematically evaluating different driving configurations, it demonstrates that a drive-stop strategy maximizes mode detection by increasing data volume and clarity, while slow driving enhances mode peak resolution. The study suggests a drive-stop strategy at a slow speed for effective drive-by monitoring of bridge vibrations.
3. The study establishes trajectory-based recommendations for comprehensive drive-by bridge mode identification. It finds that while driving along the bridge center or edges does not significantly impact bending mode detection, torsional modes are more reliably captured along the bridge edges. The study emphasizes the need for multi-trajectory runs to ensure comprehensive mode identification across various bridge types.
4. The study further proposes a conceptual approach that integrates Connected Vehicles (CVs) and mobile robots for bridge network reliability monitoring. While CVs provide continuous network-level assessments, robots equipped with multi-modal sensors offer localized precision for bridge mode identification and detailed structural assessment and evaluation. This multi-tiered

method has a promising application in accurate reliability index calculations, proactive infrastructure management, and optimized resource allocation.

Given these contributions, the following sections detail the background of the condition of civil infrastructure systems with current challenges and needs, as well as recent advances in bridge management (Section 2). Section 3 presents the relevant literature on drive-by monitoring, focusing on the use of mobile robotics. Section 4 explains the objective and scope of this study. Section 5 introduces the methodology for bridge mode identification using robot-based drive-by bridge monitoring. Section 6 details the equipment used in the study, mobile robotic platform, and portable SHM system. Section 7 provides details regarding the test scenarios and experimentation and demonstrates the real-time bridge data analysis. Section 8 presents the results of the methodology with a comprehensive discussion and potential future research directions. Section 9 discusses an integrated approach for bridge network reliability monitoring. Finally, Section 10 concludes the study with a summary and a list of conclusions.

2. Background in condition of civil infrastructure

2.1. Current challenges and needs

Aging infrastructure is a critical global challenge, particularly in the United States (U.S.), where over 617,000 bridges and other vital elements like towers, airports, dams, and waterways are under increasing strain. Reports indicate that 42% of bridges are over 50 years old, with 46,154 classified as structurally deficient, contributing to a $125 billion backlog in repairs (Iacovino et al., 2022). These deficiencies threaten economic productivity and community resilience (Luleci et al., 2024). Climate-induced events, including hurricanes, floods, and extreme weather, accelerate structural deterioration, further straining already aging systems (Wahl et al., 2017). These events often exceed infrastructure capacities, underscoring the urgent need for proactive monitoring strategies (Jamali et al., 2019). Aging and damaged structures pose significant risks to public safety, disrupt economic activities, and compromise the reliability of transportation networks (Chen et al., 2002). Addressing these challenges requires a shift from reactive to proactive management, employing advanced monitoring tools to detect and mitigate issues before they escalate, ensuring both safety and resilience in critical infrastructure systems.

The evolution of infrastructure inspections in the U.S., particularly for bridges, has been driven by historical collapses and advancements in technology (Cao et al., 2020; FHWA, 2019; Rittmeyer et al., 2022; Swenson & Ingraffea, 1991). This has led to the establishment of rigorous inspection standards, including initial, routine, in-depth, damage, and special inspections conducted by qualified inspectors (FHWA, 2012b). The most common type of inspection, initial and routine inspections, primarily rely on traditional methods, including human-based visual evaluations of structures and using tools like chain drag and hammer tapping to assess structural integrity (FHWA, 2012a). While these approaches are widely utilized due to their simplicity, they are labor-intensive, subjective, and often fail to identify subtle structural issues (National Academies of Sciences Engineering & Medicine, 2019). Periodic inspections, mandated by local and federal codes, provide a snapshot of structural conditions but lack the capability to track real-time changes or detect early-stage damage (FHWA, 2001).

In-depth, damage, and special inspections are employed when detailed assessments are necessary, occasionally utilizing advanced, technology-enabled solutions. Nondestructive Testing/Evaluation (NDT/E) techniques, such as ultrasound, infrared imaging, and ground-penetrating radar, provide high precision in identifying localized defects, making them critical for thorough inspections (Alqurashi et al., 2025; Zaki et al., 2015). However, these methods are resource-intensive, laborious, and challenging to scale across extensive bridge networks. Similarly, SHM systems, which deploy sensors for continuous monitoring of structural behavior, represent a significant advancement in proactive management (Debees et al., 2024). Due to their high implementation costs and complexity, SHM systems are prioritized for landmark structures, such as iconic or high-risk bridges, where failure would have catastrophic consequences. Despite their importance, these landmark and high-priority bridges account for only a very small fraction of the overall bridge network (Capacci et al., 2022). The majority of bridges, including long-span, medium, and small bridges critical for regional connectivity and economic activities, lack access to such advanced monitoring systems (Akgül & Frangopol, 2003). This disparity underscores the urgent need for scalable, cost-effective, and efficient solutions to manage and maintain a vast and aging bridge network effectively (Mendoza-Lugo et al., 2024). In summary, the key needs for bridge infrastructure operation and management include:

- Enhancing real-time monitoring and predictive capabilities to provide continuous insights into structural conditions, enabling early detection of potential issues and reducing the likelihood of costly and catastrophic failures.
- Creating scalable and cost-effective frameworks to extend monitoring coverage to the vast majority of aging bridges, including long-span, medium, and small structures, that currently lack adequate systems.

2.2. Recent advances in bridge assessment: drive-by monitoring

Recent years have witnessed remarkable advancements in bridge applications, leveraging technology-oriented approaches (Luleci et al., 2024). One particular area is the utilization of vehicle-based data to monitor and assess bridges. Research has shown that vibration data collected from vehicles as they drive over bridges contains valuable insights into the structural health and condition of the bridge (Malekjafarian et al., 2015). This innovative approach, termed drive-by bridge monitoring, equips vehicles with sensors to assess bridge conditions, providing a practical, scalable, and resource-efficient alternative to traditional monitoring methods (Li et al., 2024; Malekjafarian & OBrien, 2017). It is particularly advantageous for assessing large-scale bridge networks where conventional techniques are impractical or cost-prohibitive.

The growing prevalence of mobile data sources, including smartphone sensors such as accelerometers, has further propelled this approach into prominence (Li, Lan., Feng, et al., 2024; Mei & Gül, 2019; Staniek, 2021). Smartphones in vehicles collect vibration data as vehicles traverse bridges, enabling valuable insights into structural health through crowdsourcing (Matarazzo et al., 2022; Peng, Li, Hao, et al., 2023). This concept leverages data contributions from multiple users, increasing monitoring coverage and reducing costs (Yao et al., 2019). Modern vehicles, especially Connected Vehicles (CVs), are equipped with advanced sensors that continuously gather and transmit data on parameters such as speed, location, and vibration (Chen et al., 2021; Dennis et al., 2014). These data streams, particularly vibration data, are analyzed by centralized systems to identify anomalies and assess structural conditions in near real-time (Mei et al., 2020). The emergence of Electric Vehicles (EVs), which are also CVs, adds another layer of precision by delivering cleaner, engine noise-free data inputs, enhancing the accuracy and reliability of these monitoring systems.

With these advancements, drive-by bridge monitoring offers a promising pathway to more efficient and widespread bridge condition assessment to address the needs in practice as mentioned earlier: (1) real-time monitoring and early issue detection; (2) scalable and cost-effective bridge monitoring frameworks. In this context, this study investigates and experimentally validates a mobile robot-based indirect monitoring methodology on a real-world operational bridge under various driving scenarios. The research utilizes a specialized four-wheeled Unmanned Ground Vehicle (UGV, or robot, used interchangeably in this paper) equipped with multi-modal sensors to collect bridge response data and analyze it in near real-time. A simple yet practical and effective methodology is employed to ensure accurate bridge response capture as the robot traverses the bridge.

3. Relevant literature: drive-by and robot-based monitoring

This section provides a brief review of drive-by monitoring as well as the newly emerging field of robot-based drive-by monitoring by presenting some of the representative studies in the literature. The methodology of using vehicle-based responses for extracting bridge health or structural information was pioneeringly proposed (Yang et al., 2004). In that study, the authors conducted numerical simulations using a spring-mass vehicle model and a simple supported beam to simulate the Vehicle-Bridge Interaction (VBI) process. It was found that the bridge's fundamental frequency could be identified from the accelerations of the vehicle body. This concept was later validated in 2005 through field tests conducted (Lin & Yang, 2005), which involved a tractor-trailer vehicle system and one span of the Da-Wu-Lun Bridge in Taiwan. Subsequently, the approach was extended to assess bridge conditions (Bu et al., 2006; Hester & González, 2015; Kim & Kawatani, 2008). These pioneering studies laid the foundation for using vehicles as moving sensors for monitoring and assessment of bridge infrastructures, inspiring further research within the scientific community.

Over the past two decades, many studies have investigated the extraction of bridge information from vehicle responses through the VBI process using numerical simulations, laboratory experiments, and involving a few field tests (Malekjafarian et al., 2022; Singh et al., 2023; Xu et al., 2024). As a foundational aspect, identifying bridge frequencies from vehicle accelerations has been a primary focus, as it forms the basis for advanced applications such as damage detection and bridge residual life prediction (Corbally & Malekjafarian, 2021; Li, Lan., Feng, et al., 2023).

Following the initial efforts in 2004 (Yang et al., 2004), researchers examined the effects of vehicle parameters, various signal processing techniques, and specially designed vehicles on the indirect identification of bridge frequencies (Jin et al., 2022; Li, Zhu, et al., 2022; OBrien et al., 2017; Yang, Li et al., 2022; Yang & Chang, 2009). However, two major challenges emerged during this process: (1) The interference caused by road roughness; and (2) The influence of the vehicle's own dynamic fingerprints within its responses. Solutions such as CVs, tapping scanning techniques, and vehicle amplifiers were explored to mitigate the impact of road roughness (Hu & Xiang, 2024; Jian et al., 2020; Kong et al., 2016; Xu et al., 2023). Despite these efforts, practical challenges remain. Large-scale management of CVs in operational settings can be challenging due to substantial amounts of data (He & Yang, 2022; Yang, Li, Wang, et al., 2022), while tapping scanning and vehicle amplifier methods often require vehicle modifications to suit bridge monitoring tasks. Addressing the issue of vehicle dynamics interference, researchers have applied various filters to isolate and remove vehicle frequencies from the data (Shirzad-Ghaleroudkhani & Gül, 2021; Y. B. Yang et al., 2013).

However, this typically requires prior knowledge of the vehicle's parameters. To overcome these limitations, the concept of Contact Point (CP) responses was introduced (Yang et al., 2018). CP responses represent the accelerations, velocities, or displacements at the contact points between the vehicle and the bridge, making them independent of the vehicle itself and solely influenced by road roughness and bridge vibrations (C. Liu et al., 2023; Singh & Sadhu, 2023). Despite its promise, deriving CP responses from vehicle data often requires precise measurements of the vehicle's parameters (Corbally & Malekjafarian, 2021; Feng et al., 2023), which poses significant barriers to practical implementation. Consequently, there is an urgent need for a new, practical technique that enables rapid estimation of bridge modal parameters and facilitates effective bridge assessment.

In the last few years, with the advancements in hardware and signal communication technologies, robot-based assessments (Sony et al., 2019) have been a prominent topic in infrastructure health monitoring, assessment, and maintenance (Charron et al., 2019; Jahanshahi et al., 2017; Luleci et al., 2024; Sony et al., 2019; Tian et al., 2022). Robots can be categorized as Unmanned Ground, Aerial, and Underwater Vehicles (UGVs, UAVs, UUVs) in the context of infrastructure operation and maintenance. In this review, the use of UGVs (Luleci et al., 2024) is emphasized, rather than UAVs (Bolourian & Hammad, 2020; Zhao et al., 2021) and UUVs (Tsaimou et al., 2024; Waldner & Sadhu, 2024). In 2012, a study (Zhu et al., 2012) proposed Flexure-Based Mobile Sensing Nodes (FMSN) for system identification of a space frame bridge. This system utilized several magnetic wall-climbing robots that moved along the smooth surfaces of steel structures. Compared to traditional sensing networks on bridges, the frequencies extracted by FMSN could provide reliable measurements.

In 2014, another work (La et al., 2014) developed a robotic nondestructive evaluation system for bridge deck inspection. The system integrated various tools, including surface cameras, ground-penetrating radar, acoustic arrays, and GPS. Experimental results demonstrated the robot's ability to map deck cracks, corrosion, delamination, and concrete modulus effectively. In 2018, researchers introduced a mobile robot-based damage localization method using an adaptive Monte Carlo approach (Peel et al., 2018). The DiddyBorg robotic platform they developed was also employed to calculate the geometry of bridge bearings.

Moreover, the use of robotics in infrastructure health monitoring has expanded to include inspections of other bridge components and underwater structures (Gucunski et al., 2017). For instance, in 2020, one study (Jang et al., 2021) designed a ring-type climbing robot to evaluate high-rise bridge piers automatically. Their results showcased the ability to create detailed digital crack maps of the target bridge pier. Additionally, another work (Jiao et al., 2024) designed a robot powered by hybrid driving methods, including combustion-based actuators and propeller thrusters. Using camera images processed with the YOLO (You Only Look Once) algorithm, they successfully identified various damages in underwater concrete structures. The existing literature highlights the growing importance and effectiveness of robotics in infrastructural condition assessment.

Recently, a few other studies have begun considering robots for the indirect monitoring of bridges. In 2016, researchers (Marulanda et al., 2017) employed a movable and stationary robot equipped with accelerometers to identify bridge modal parameters. They successfully identified frequencies and modal shapes of an I-shaped beam subjected to ambient vibrations in a laboratory setting. In 2019, researchers (Mei et al., 2019) developed a simple robotic car to simulate a spring-mass vehicle and used a steel plate as the bridge deck in the laboratory. Mel-frequency cepstral coefficients were extracted from robot accelerations as damage indicators, and experimental results validated the effectiveness of the proposed method. In 2023, another study (Shirzad-Ghaleroudkhani & Gül, 2024) equipped a robotic car with a smartphone to collect various signals. This work accounted for operational effects such as engine vibrations, suspension system dynamics, and road roughness. An inverse filtering method (Shirzad-Ghaleroudkhani & Gül, 2021) was applied to mitigate the impact of these factors and emphasize bridge-related information. In the same year, researchers (Peng et al., 2023) extended indirect bridge health monitoring to an Internet of T-enabled framework by incorporating wireless accelerometers, temperature sensors, GPS, and a 4 G communication module on a robotic vehicle. A more recent study (Jian et al., 2024) introduced a low-cost robotic framework using Robo-Master EP. By combining stationary and mobile sensors on the robot, the study successfully identified the first two modal shapes of a footbridge.

Studies in the literature highlight the significant potential of indirect bridge monitoring for bridge assessment with promising both theoretical and analytical approaches. Though this research area is rapidly progressing, much of the research remains confined to numerical simulations and laboratory experiments, with limited field tests conducted in real-world operational conditions. This gap hinders the transition of these methodologies from conceptual frameworks to practical applications. Proposed methods often face challenges related to scalability, implementation, and adaptability to diverse conditions, limiting their real-world applicability. Additionally, while robot-based approaches have shown promise, their use in infrastructure assessment has been relatively limited. Specifically, the application of robots for indirect bridge monitoring is a new but rapidly evolving research area with significant potential to overcome existing barriers. However, this field is still in its early stages and requires further exploration to develop innovative, scalable, and cost-effective solutions for practical bridge condition monitoring.

Unlike previous studies that primarily relied on small robotic platforms in controlled environments, this study advances the field by implementing a field-tested UGV-based drive-by SHM approach and demonstrating its feasibility on real-world infrastructure. A key innovation of this work is the filtering-based methodology, which isolates bridge response from drive-by data by mitigating the effects of road roughness, vehicle-induced dynamics, and other noise sources in the frequency domain. This approach enhances bridge mode identification by making true bridge mode peaks more distinct, eliminating false peaks, and enabling the detection of additional bridge modes previously undetectable. Furthermore, this study systematically evaluates various robot-driving strategies, establishing that a drive-stop approach at slow speeds maximizes mode detection by improving data clarity and peak resolution. Additionally, robot trajectory-based recommendations are introduced, highlighting that torsional modes are best captured along bridge edges while bending modes remain unaffected by lateral positioning, emphasizing the need for multi-trajectory for optimum bridge drive-by monitoring. Beyond individual bridge monitoring, this study envisions a network-level approach by integrating UGV-based monitoring with CV, where CVs provide continuous large-scale assessments while mobile robots enable localized, precise evaluations. This multi-tiered framework lays the groundwork for scalable, proactive, and efficient infrastructure health monitoring, moving beyond isolated bridge assessments toward comprehensive network reliability monitoring.

4. Study objective and scope

Given the review and the identified research gaps as outlined in Section 3, the overarching objective 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. Under this central objective, the study defines several specific objectives. The first one seeks to investigate a simple but effective data processing approach to mitigate the interference of road roughness and vehicle dynamics in order to isolate the bridge response for bridge mode identification. Additionally, the study aims to explore the impact of varying driving speeds, drive-stop scenarios, and the robot's trajectory on different sides of the bridge to determine the optimal conditions for precise bridge mode identification. The study further investigates the dual capability of integrating real-time mode identification with visual data capture and analysis over the bridge using robot-based drive-by monitoring to emphasize its potential to support rapid decision-making and early detection of structural condition changes. In summary, this study aims to advance the field of indirect bridge monitoring and support the widespread adoption of mobile robotic platforms in infrastructure monitoring by addressing these key objectives.

In the process of achieving these objectives, the study scope is limited to several factors, as given in the following: (1) The methodology is applied to a single test environment, which includes a pedestrian bridge and a limited length of connecting adjacent roads. (2) The study's methodological approach investigates a practical and scalable drive-by monitoring solution, hence, it does not consider vehicle parameters. (3) The mode identification process is limited to bridge natural and operational frequency identification. (4) The robot is limited to two steady speeds (slow 0.4 m/s and fast 1.0 m/s), which will be the robot speed rates during tests. (5) Driving on different trajectories on the bridge is limited to three path, south, middle, and north sides of the bridge as the drive coverage amount of the bridge is deemed sufficient. (6) No structural damage scenario or a decision-making mechanism is considered in the tests, which will be further reflected in the future studies.

5. Methodology to identify bridge modes *via* robot

Before a vehicle enters a bridge, it also has the opportunity to collect data from the adjacent roadway connecting the bridge. This data collected from the road can then be used as a reference for filtering the data collected from the bridge, potentially enabling the isolation of the bridge's response, which is critical for identifying its vibration modes. Such a methodology can be very practical in real-world applications and possible to achieve under certain assumptions, such as the same driving conditions and road surfaces for both on the road before entering the bridge and over the bridge. While the same driving conditions (e.g., driving at the same steady speed) can be maintained before and over the bridge, it can be difficult to have identical road (pavement) surfaces for both.

Authors preliminary investigations conducted in a controlled, real-world environment, with data collected on asphalt and concrete surfaces, as typically bridge road surface material is concrete rather than asphalt, suggest a no-to-minimal difference in the frequency domain of both the data collected from road and bridge (see Figure A1 in Appendix), indicating the successful potential of implementing this methodology in real-world cases. While these initial findings are informative, a more comprehensive analysis is necessary to validate the methodology and its assumptions.

This paper's methodology is illustrated in Figure 2 and involves the following steps: (1) Data collection from both the roadway and the bridge. (2) Matching the data lengths if they are unequal to ensure compatibility for frequency domain operations and analysis. (3) Performing a Fast Fourier Transformation (FFT) on both signals to transform them into the frequency domain. (4) Scaling the amplitudes of the frequency spectra of the data collected from road to align it with the data collected from the bridge or the other way around. (5) Filtering the frequency spectrum of the bridge data using the amplitude spectrum of the road data to isolate the bridge's response in the frequency domain. (6) Identifying the vibration modes of the bridge structure using the isolated bridge data.

There are several external factors influencing the vibration data collected by the vehicle as it traverses over the bridge, such as road surface/pavement roughness, vehicle characteristics (e.g., vehicle engine, suspension, tire, vehicle structural natural frequency - note that robot's natural frequency band was identified in the 12–15 Hz ranges by applying a tapping force on the robot's structure, see Figure A2 in Appendix), driving speeds (e.g., slow, fast), and other noises (e.g., wind, nearby vibrations, electromagnetic interference, or measurement noises). The goal is to isolate the bridge response from these external influences to leave the intrinsic vibration characteristics of the bridge alone for accurate mode identification, which is typically carried out in the frequency domain. The decomposition of complex signals into their frequency domains facilitates clear identification of natural frequencies associated with the bridge structure. When data is collected by a vehicle traversing over a bridge, the measured signal from the bridge in the frequency domain, denoted as $H_B(f)$ is represented in equation:

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

where $H_b(f)$ represents the bridge response in the frequency domain, $H_r(f)$ the road response, $H_v(f)$ the vehicle

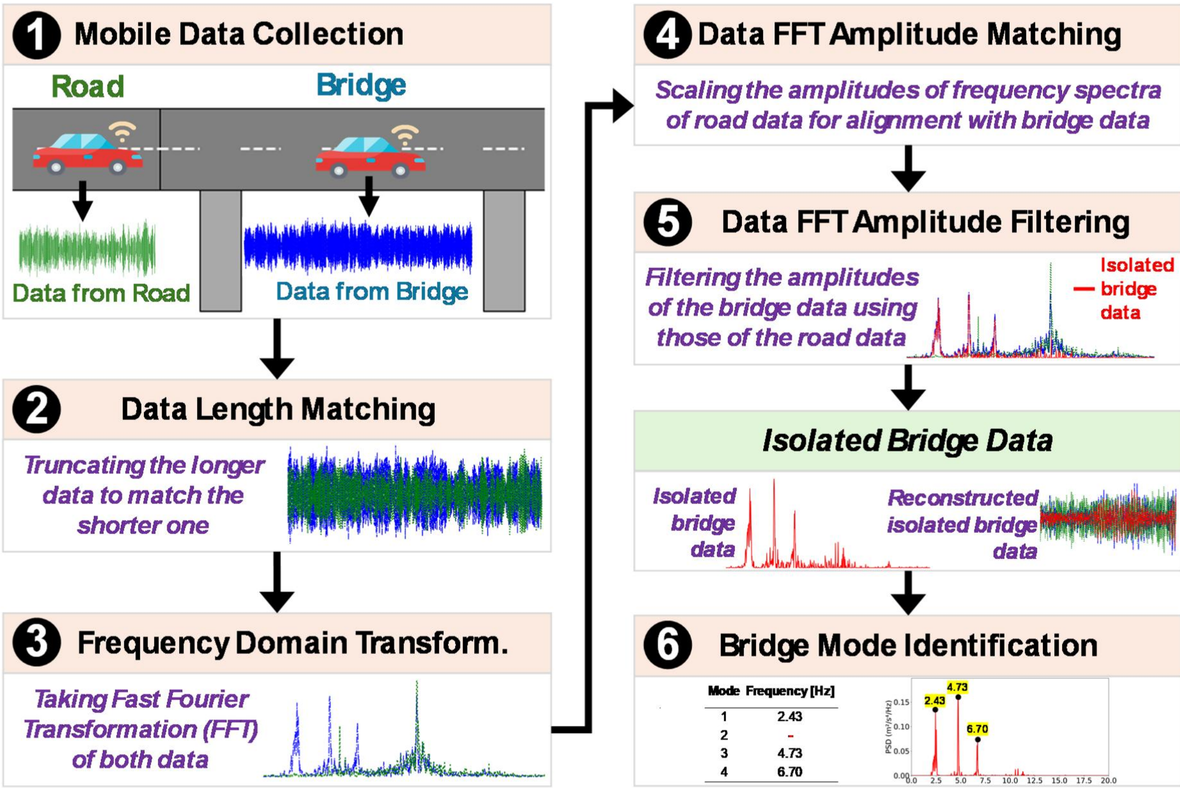


Figure 2. Methodology to identify the bridge vibration modes. Each methodological step from 1 to 6 can be followed in the following subsections in the same numbering order.

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:

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

These representations, Equations (1) and (2) assume linear superimposition, where the measured signal is treated as the sum of individual contributing components; an extensive discussion about this is made in Section 8. In addition, for this methodology to work theoretically, the speed of the vehicle must be identical on both roads and bridges. During the tests it was noticed that the frequency domain changed when the speeds varied, as changing speeds caused shifts in the data. However, the impact of changing road and bridge surface materials on the data needs to be examined further. For this reason, it is assumed in this study that the material of the road surface and bridge road surface must be identical for this methodology to work, which is the case in the presented test environment. This is further discussed in Section 8.

5.1. Data collection

The data collection process is simply the vibration data collection by the vehicle as it traverses the road before and over the bridge. In this process, it is vital to have an equal length of data from the road as the data from the bridge so that the operations and analysis in the frequency domain can be achieved accurately. While this methodology only considers the data from the road before entering the bridge, the combination of data from both roads (and then possibly averaging in frequency domain later, which could make it more robust based on how different the road surfaces are from the bridge roadway surface) or the data only from the road after exiting the bridge can be considered for later operations and analysis. Nevertheless, it is essential to have an equal length of data from both data sources. If not, the longer data source is truncated to match the shorter one. Note that the mean removal process is implemented for all the data collected.

5.2. Data length matching

Three methods were tested in data length matching before choosing the suitable method: (1) resampling the shorter signal, (2) zero padding the shorter signal, and (3) truncating the longer signal. It was observed that the application of resampling and zero padding yielded less favorable results. The resampling technique introduced interpolation artifacts that affected the signals' frequency domain results. The zero padding method caused spectral leakage and edge effects in the data, which introduced discontinuities in the frequency domain. However, the authors speculate that generative artificial intelligence models (Luleci et al., 2023; Luleci & Catbas, 2023) can be utilized to extend the shorter signal.

The methodology herein employed data truncation for simplicity. During the experimentation, due to the shorter length of the road than the bridge, the data from the bridge was truncated to match data measured at the road. In the process, it was ensured that the data from the bridge was truncated from both ends of the signal (near fixed-end parts of the bridge) to leave the mid-parts of the data as much as possible so that the semantically richest part of the data about the bridge was untouched. Both the frequency domains of truncated and untruncated data were then compared to ensure the truncated data measured from the bridge contained the same relevant bridge information as the untruncated one. Overall, this truncation process requires supervision or a controlled automation process in real-life procedures. However, this will not be required in real-world settings because there will be sufficient data from the roads, so matching the data length will not be needed.

5.3. Frequency domain transformation

Following the data length matching process, the data from the bridge and truncated data from the road are transformed into their frequency domains by taking their FFT. This enables the subsequent operations in the frequency domains of these data.

5.4. Data FFT amplitude matching

The FFT amplitudes of the truncated data from the bridge and data from the road are matched by scaling the amplitudes of the road one, which could also be implemented in another way. The scaling process is applied to avoid discrepancies in the FFT amplitude range that could lead to incorrect results in the subsequent filtering process, as the amplitude ranges of the two data sources are not inherently the same. Thus, to make both data consistent, the FFT amplitude range of the data collected from the road is scaled to the range of truncated data measured from the bridge. The computation process is presented in the following paragraphs.

The amplitude spectra for both signals are calculated as the magnitudes of the FFT results using equation:

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

where $|H(f)|$ is the amplitude spectra of the data computed (bridge or road), and $Re(\cdot)$ and $Im(\cdot)$ are the real 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:

$$Scaling\ \ Factor = \frac{\sum_{k=0}^{N/2} |H_{B,\,trunc}(f)|}{\sum_{k=0}^{N/2} |H_R(f)|} \tag{3}$$

where N is the total number of samples in the time-domain signals, and $|H_{B,\,trunc}(f)|$ represents the amplitude spectra of the truncated bridge data, computed from an FFT of an N-sample signal. The summation in Eq. (3) is performed over the positive frequency components up to N/2, as only positive frequency bins of the FFT are considered. Then, the amplitude spectrum of the data collected from the road $|H_R(f)|$ is scaled using the computed scaling factor as in equation:

$$|H_{R,\,scal}(f)| = Scaling\ \ Factor \cdot |H_R(f)| \tag{4}$$

where $|H_{R,\,scal}(f)|$ is the amplitude spectrum of the data (collected from the road) after scaling.

5.5. Data FFT amplitude filtering

Following the amplitude matching, a filtering process is implemented in the frequency domain. Specifically, the amplitude spectra of the scaled road data $|H_{R,\,scal}(f)|$ are used to filter the truncated bridge data $|H_{B,\,trunc}(f)|$ element-wise, thereby isolating the amplitude spectra of the bridge response $|H_b(f)|$, as presented in Eq. (5). As a result of this computation, other components involved in $|H_{B,\,trunc}(f)|$ are then also removed (Eq. (1)), such as road, vehicle, speed, and noises, due to being the same in the data collected from the road:

$$|H_b(f)| = |H_{B,\,trunc}(f)| - |H_{R,\,scal}(f)| \tag{5}$$

Then, the isolated bridge response full frequency spectrum is reconstructed by combining the amplitude $|H_b(f)|$ with the original phase $\angle H_B(f)$ of the bridge data in equation:

$$H_b(f) = |H_b(f)| \cdot e^{j\angle H_B(f)} \tag{6}$$

where $e^{j\angle H_B(f)}$ encodes the phase of the frequency response. Following this operation, the isolated bridge frequency spectrum $H_b(f)$ can be converted back to the time domain utilizing the inverse FFT technique.

5.6. Bridge mode identification

The isolated bridge response frequency spectrum $H_b(f)$ is then utilized to identify the vibration modes of the bridge. For this particular task, the Power Spectral Density (PSD) of the bridge response is calculated, which takes the square of the magnitude of the frequency spectrum $|H_b(f)|^2$ and normalizes it by the frequency bandwidth to represent the power per unit frequency. This process ensures that the energy content of the signal is accurately distributed across its frequency range, regardless of the data length or sampling rate. The PSD is chosen to identify vibration modes because it highlights dominant frequencies more effectively, even in the presence of noise or weaker signals. The normalization provides a clearer and more reliable view of the energy associated with each frequency.

For the rest of the study, the RMS (Root Mean Square) of the PSD was utilized as a guiding statistical baseline for identifying 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 σ when the signal has zero mean, which is the case. In this context, the use of $2 \times RMS$ (or 2σ) as a threshold for identifying peaks corresponds to capturing approximately 95.4% of the energy within the signal, based on the properties of a Gaussian distribution. This ensures that peaks exceeding this threshold are statistically significant deviations from the noise floor, minimizing the likelihood of false positives while guiding us to capture relevant vibration modes. The choice of using 2σ instead of 3σ reflects a balance between sensitivity and specificity as 3σ captures 99.7%, which would be more restrictive. Both thresholds (2σ and 3σ) were tested and it was observed that using these thresholds in guiding for identifying the modes did not influence results for this dataset. Overall, this $2 \times RMS$ threshold guides us on which peaks to take into consideration during the mode identification process.

6. Equipment used for test

In testing the methodology for different experimentation cases, this study utilized a four-wheeled UGV equipped with multi-modal sensors to collect the response data from the test road and bridge (as mentioned earlier, only the onboard accelerometer was utilized for drive-by monitoring in this study). For benchmarking purposes of the data collected from the robot over the bridge, the study also utilized a portable SHM system with cabled accelerometers installed at the bridge during the test. The following paragraphs introduce the details of the test equipment.

The UGV, named Cypector (Cyber + Inspector), is based on the Husky model (A 200) robot manufactured by Clearpath Robotics and designed by Civil Infrastructure Technologies for Resilience and Safety (CITRS) at the University of Central Florida. Cypector is a 4-wheeled UGV featuring a robust wheeled chassis. In this study, Cypector has been enhanced with additional accessories, some mounted on the top plate and others placed underneath, as depicted in Figure 3. These accessories include two VLP-16 LiDARs from Velodyne, an ADK Infrared Camera and two Blackfly S Cameras from FLIR, a GPS-18x from Garmin, a ZED 2 Stereo Camera from Stereolab, an Omni 60 360 Camera from Occam, a Gigabit Wireless Router, and a GPU-enabled Mini-ITX computer and an IMU (Internal Measurement Unit) from Microstrain 3DM-GX5-25, located beneath the plate.

Furthermore, Robot Operating System (ROS) (ROS 1) serves as the middleware framework for Cypector, providing a collection of open-source tools and libraries that facilitate seamless communication between software and hardware. ROS abstracts hardware complexities and manages communication between various physical devices and software components installed on the robot. This is achieved through device drivers that interface with hardware components like Cypector's accessories. For user interaction, Cypector broadcasts a Service Set Identifier (SSID) from its access point (router), which is connected to the robot's internal computer. The user can connect to this SSID, after which an IP address is assigned to the user's computer *via* static or DHCP methods. Once connected, the user can access Cypector's internal computer through SSH to control and operate the robot.

The response data collection from the road and bridge is achieved using this onboard IMU sensor in Cypector, which is capable of collecting 3-axis vibrations, with vertical vibrations being the primary focus in this study due to their critical role in structural response characterization. IMUs play an integral role in robotics, providing essential data on acceleration and angular velocity to estimate position, orientation, and motion. As a fundamental component in almost all robotic systems, IMUs ensure navigation and stability, which are indispensable for tasks that require accurate environmental interaction and control. In this study, the IMU is not only used for data acquisition for bridge mode identification but is also needed for Cypector's operational use and reliability.

Table 1 presents the datasheet of the sensors utilized in the experiments regarding their relevant accelerometer capabilities. As mentioned earlier, the Microstrain 3DM-GX5-25 IMU sensor is equipped in the robot, facilitating the vibration data acquisition. On the other hand, for the reference monitoring dataset from the bridge, the PCB M603C01

Figure 3. Cypector (mobile robot) and its multi-modal sensors and other equipment.

Table 1. Datasheet of the accelerometer sensors used in the tests: PCB M603C01 and Microstrain 3DM-GX5-25 IMU within the robot.

Image	Sensor	Measurement range	Resolution	Non-Linearity	Noise density
	PCB M603C01	±50 g	350 μg	±1 %	5 μg/√Hz
	Microstrain 3DM-GX5-25	±40 g	0.02 mg (+/− 8 g)	±0.02 %	20 μg/√Hz (2 g)

Table 2. Experimentation scenarios (*J* and *S* denote jumping and stop, respectively, while the numbers *0.4* 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	0.4 m/s	Mobile Robot (Cypector) equipped with multi-modal sensors
		2		
		3		
J1	Mobile Robot	1	1.0 m/s	
		2		
		3		
J1S	Mobile Robot	1	1.0 m/s & Stop	
		2		
		3		

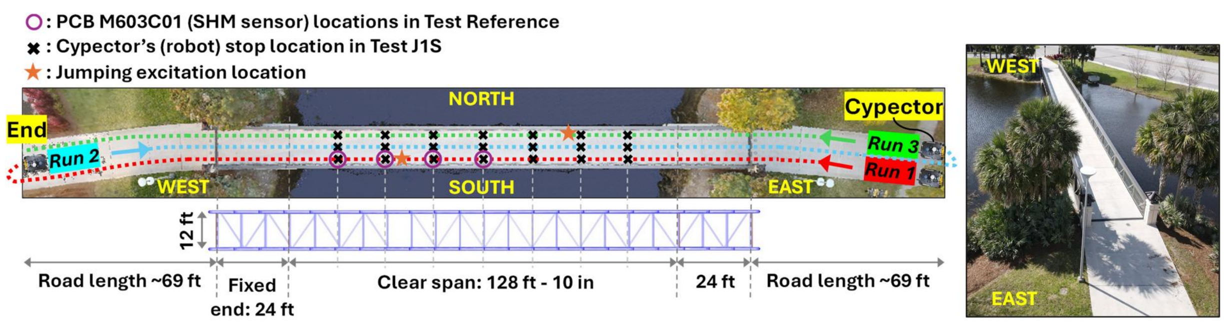


Figure 4. Illustration of the bridge test setups.

accelerometer sensors were used, connected to the NI 9234 module within the National Instruments (NI) cDAQ-9178 chassis.

7. Experimentation scenarios and some remarks

The following paragraphs provide a comprehensive overview of the experimentation setups, detailing the scenarios designed to evaluate the methodology and identify bridge vibration modes, along with real-time drive-by details from the tests and additional remarks on tests. Table 2 summarizes the experimentation scenarios, while Figure 4 illustrates the test setups and sensor configurations. The reference test utilized a portable SHM system equipped with PCB accelerometers installed at four strategic locations on the bridge (see Figure 3 for sensor locations) conducted under a hammer-tapping excitation. These locations were chosen to capture both bending and torsional modes, which constitute the majority of the structural modes of the test bridge.

For the tests involving the robot, three distinct driving scenarios were considered: slow driving at 0.4 m/s, fast driving at 1.0 m/s, and a combined drive-and-stop case at 1.0 m/s (each stop is for 10 s and seven stops along the bridge). These scenarios were designed to investigate the impact of varying driving speeds on mode identification results, with 0.4 m/s and 1.0 m/s representing the lowest and highest steady speeds achievable by Cypector. Each test scenario was conducted in three separate runs, with the robot traversing different sides of the bridge (each run aligned with the corresponding side of the road) to evaluate whether driving on different sides influenced the mode identification outcomes.

Additionally, excitation was applied to the bridge by having two people asynchronously jump at specific locations during the drive-by test (two opposite sides of the bridge to enable torsional dynamic impact on the bridge—see Figure 4). This applied excitation, two people jumping at separate locations, was chosen to simulate the operational conditions this bridge regularly experiences, such as student jogging and running. This approach was necessary, as relying on the timing of natural pedestrian activity proved impractical for the drive-by testing. Note that an initial test conducted included a no-excitation (ambient) scenario; however, this case was set aside for more focused future

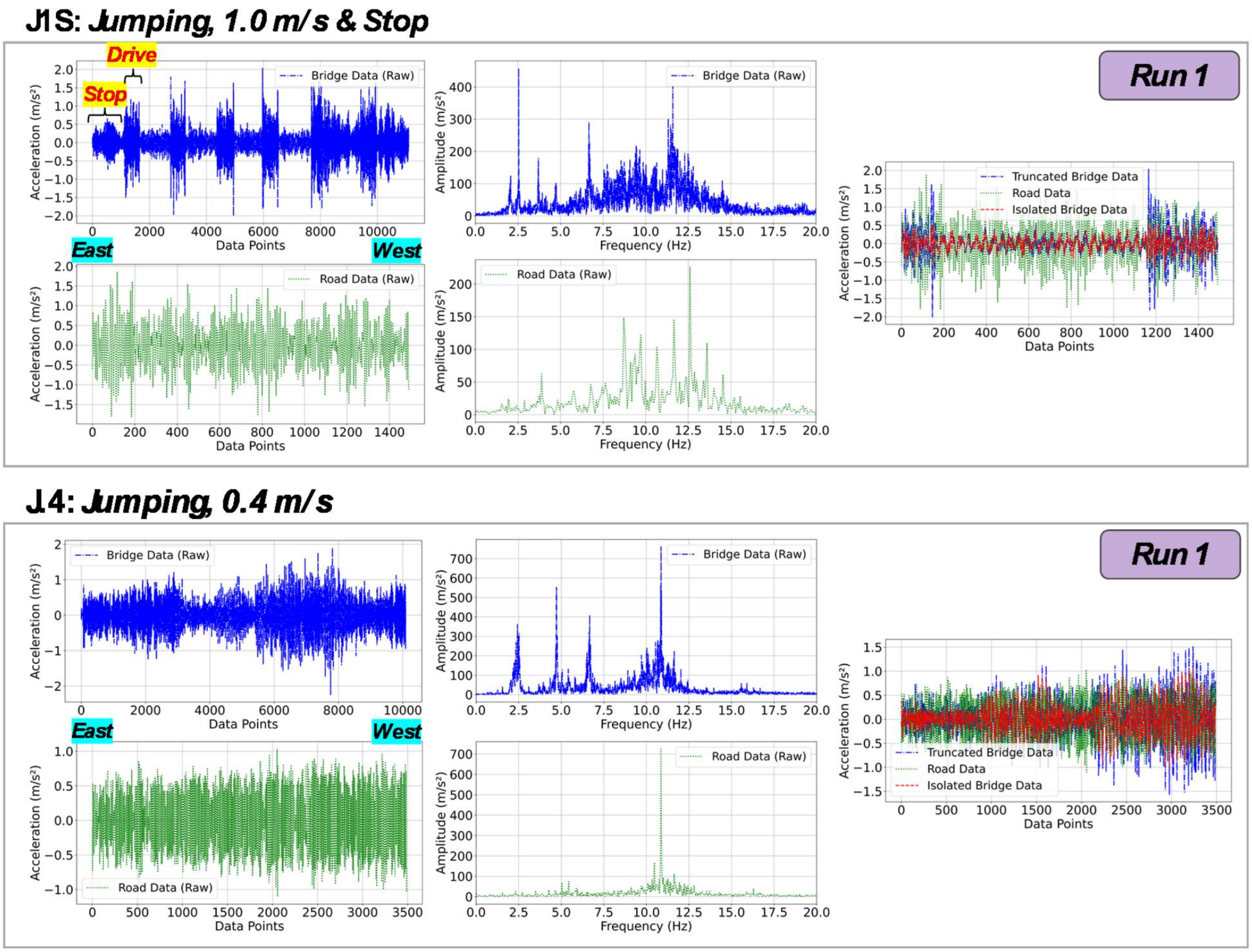


Figure 5. Some of the bridge and road data in the time and frequency domains.

analysis due to the limited identification of vibration modes, capturing only up to two modes.

Tests are conducted in order, starting with the Reference test and then J.4, J1, and J1S. Figure 5 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 the Run 1 cases of J1S and J.4. In the J1S scenario, the drive and stop periods are distinctly observable. 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. As the robot speed increases, this peak broadens, spreading across the frequency range of 8 Hz to 13 Hz, overlapping the bridge's 5th and 6th modes. Further discussion and analysis are provided in the next section.

During the test, the vibration response data collected by the robot are monitored in real-time, in the time and frequency domains, successfully identifying some of the bridge vibration modes in all the tests. Figure 6 highlights an example of this real-time mode identification, showing the 1st and 2nd modes over a specific data collection period as the robot traversed the bridge (this is for the J.4 test, Run 3). The robot's visual sensors, including its stereo camera and LiDARs, were further used for robot navigation and to track its surroundings and path, as visualized in Figure 6. The figure shows real-time images captured from the stereo camera and the point cloud generated by the LiDARs (both vertical and horizontal). This dual capability of simultaneously capturing and analyzing the vibration and visual data at the bridge in real time highlights the potential of robot-based indirect monitoring to facilitate rapid decision-making and early detection of bridge structural condition changes.

Although CVs and other sensor-equipped vehicles can also perform real-time monitoring, each has distinct advantages that make them valuable in different aspects of bridge assessment. CV-based drive-by monitoring can excel at providing widespread, general assessments of bridge networks due to their ability to collect data on a large scale. Their continuous operation across diverse routes makes them highly scalable for monitoring trends and identifying areas of concern over extensive infrastructure networks. However, the use of robots introduces critical advantages that enhance the reliability and precision of bridge mode identification for further detailed (localized) investigations. Robots are designed to follow precise, repeatable trajectories, ensuring consistent, high-quality data collection

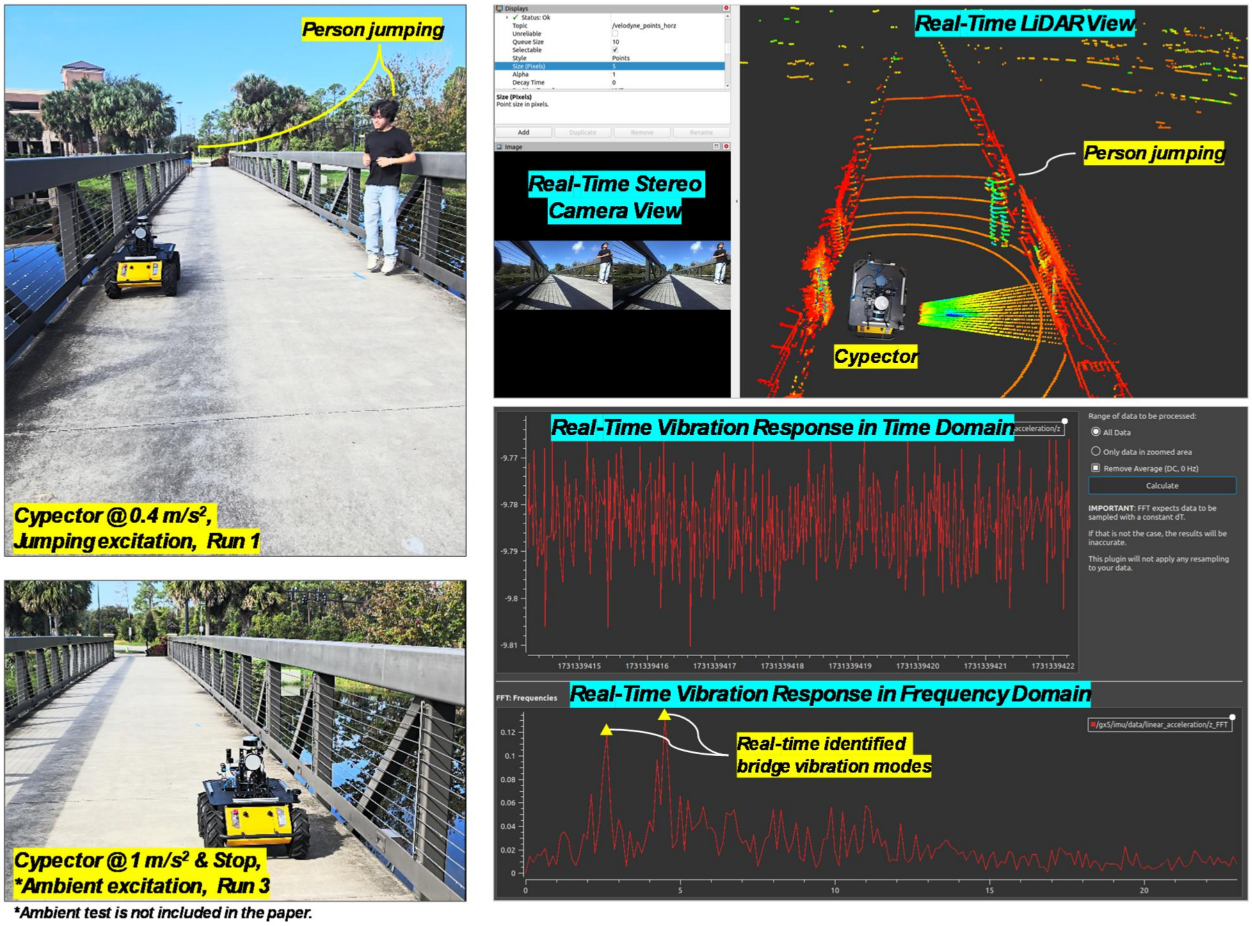


Figure 6. Some of the test visuals: Pictures taken during the test, real-time identified bridge vibration modes, and visuals including point cloud data and images captured by the robot's LiDARs and stereo camera.

unaffected by traffic variability. Purpose-built for monitoring tasks, they operate at adjustable speeds and carry advanced multi-modal sensors like Cypector has, which enables simultaneous vibration and visual data capture with potentially improved accuracy. Additionally, robots are not affected by noise from vehicle dynamics, such as suspension or engine vibrations, and can operate in conditions where CVs are unsuitable, including bridge closures, low-speed monitoring, or accessing hard-to-reach areas such as suspension bridge ropes, towers, or the underside of the deck, which can be examined using climbing robots (Jang et al., 2021).

The complementary strengths of CVs and robots suggest that the best approach would involve their combined use. CVs could be utilized for general network-wide monitoring, quickly identifying potential issues, while robots could provide in-depth, targeted assessments of identified hotspots. This integrated strategy would maximize efficiency and accuracy and offer a comprehensive solution for effective bridge monitoring and maintenance. Further discussion on this is presented in Section 9.

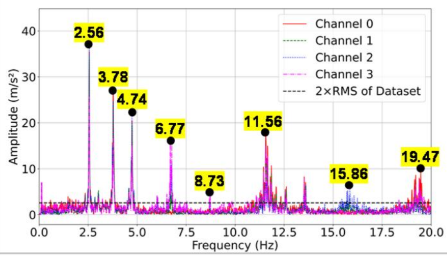
8. Results and discussion

This section presents the results alongside a detailed discussion and analysis. First, the mode identification results from the reference test are presented in Figure 7. To validate the current test, which is named reference SHM dataset (2024), the identified bridge modes were benchmarked against a past dataset collected in 2022, which was carried out under a more extensive testing setup. As shown in the figure, up to eight vibration modes were identified in the current dataset, with frequency variations of up to approximately 1% compared to the past dataset. These slight variations may be attributed to unknown structural changes, weather conditions, or testing-related errors. Despite these minor discrepancies, the mode identification results for the current reference dataset (2024) are deemed reliable and serve as a robust baseline to validate this study's methodology for robot-based drive-by monitoring. The peak between 12.5 Hz to 15 Hz in the current test (2024) does not appear in the appear in the past test (2022). This peak may be a new mode, but this is unlikely due to the fact that authors also did not observe this peak clearly in the drive-by results, as presented in the next figures. This will require a further investigation. It should be noted that the scope of this study is limited to identifying bridge frequencies and does not extend to analyzing mode shapes.

Next, the mode identification results from the robot-based indirect monitoring tests (J.4, J1, and J1S, as indicated in Table 2) are presented in the following figures, Figure 8-10. Each figure presents the results for three

Current Reference SHM Dataset (2024)

Portable SHM System w/ 4 Channels



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

Legacy Reference SHM Dataset (2022)

Ultra-Sensitive SHM System w/ 30 Channels

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

different runs (Run 1–3, each on different sides of the bridge; see Table 2 and Figure 3), and for each run, three plots and a table are presented in an analysis order. Following the arrows in a clockwise direction, the first plot presents the frequency domain (FFT) visualization of the truncated bridge data, road data, and isolated bridge data (which was also truncated due to the truncation applied to the bridge data). The second plot shows the frequency domain visualization (but in PSD) of only the truncated bridge data, where the bridge modes were identified to compare them with the mode results on the isolated bridge data (next plot) to evaluate the paper's methodology. The third plot shows the PSD of the isolated bridge data along with the identified modes. Then, the modes identified from the isolated bridge data and their differences from the reference test dataset (2024) are listed in the table next to the plot.

Considering all nine tests conducted through robot-based drive-by monitoring using the methodology proposed in this study, the first six modes of the bridge were identified with a variation of up to 7% compared to the reference test, with an overall average variation of 2%. Overall, for every run in each scenario (J.4, J1, J1S), the robot was able to capture at least three modes, with an average mode identification error rate "for each scenario" at 2%. From the results, it can be seen that in the J1S case, more modes were identified in total (10 modes), and then J1 and J.4 (9 modes each). It is noted that making stops (seven stops) as the robot traverses the bridge helped the robot capture more data, particularly clean data. Still, due to the fast drive speed (1.0 m/s) throughout the bridge, the clarity of the data was low, making it difficult to identify the mode peaks, which could potentially lead to selecting the wrong peaks as modes. These false modes (wrong peaks) are highlighted in Figure 9-10 as they overlap with the actual bridge mode (modes 5–6) since it is known from reference dataset (see Figure 7). The remaining peaks (which are named residuals, explained in the next paragraphs) do not overlap with a known bridge mode; thus, they are not highlighted. Furthermore, the authors hypothesize that the ideal scenario for capturing more bridge modes with more distinctive peaks would be the case of drive-stop at a slower speed (0.4 m/s) rather than a fast one. In summary, among the three scenarios, the J.4 case provided the clearest mode peaks in terms of data clarity, while the J1S scenario captured the highest number of modes.

Driving on the sides or in the middle of the bridge did not make a significant difference in mode identification results. While it is generally anticipated that driving along the middle of the bridge would more effectively capture bending modes, and torsional modes would be more pronounced when driving along the sides, the findings indicate a more nuanced outcome. If each scenario is examined individually, in every Run 2 (middle), torsional modes are generally missing. On the other hand, in Run 1 (south side) and Run 3 (north side), both torsional and bending modes appeared at the same number of identified modes overall. However, this will likely differ based on bridge type, as the flexibility and geometry of the bridge can influence different mode capture based on the robot trajectory on the bridge. For example, in stiffer bridges with localized vibrations, detecting certain modes depends heavily on the robot's trajectory, while in more flexible bridges, modes are more uniformly distributed, which enables easier detection across trajectories. Thus, conducting runs along all sides of the bridge would be the best practice to ensure comprehensive mode identification, particularly when dealing with diverse bridge structures.

When the robot is at a slow speed, there are a few irregular peaks around 11 Hz in the frequency domain of the road data. However, this small range irregularity spreads across to a larger range of 8 Hz to 13 Hz when the robot speed increases, overlapping the bridge's 5th and 6th modes, as evident in the FFT plots shown in the figures (Figures 5,8-10). This irregularity is caused by road data $H_R(f)$, which contains information about the robot's dynamics, driving speed, and noises (Eq. (2)). As seen in the figures, the paper's methodology effectively filters the road data $H_R(f)$ from the bridge data $H_B(f)$, thereby discarding interfering components such as vehicle effects, speed variations, and noise, and isolating the bridge response $H_b(f)$. Without the isolation methodology, identifying modes can be challenging due to the involved irregularities in the frequency domain, and this could lead to potentially selecting false modes like those noted in the J1 and J1S test cases (Figures 9-10), a total of four false modes.

Moreover, while the fundamental (first) mode, and in some cases, the second and third modes, were visible in the unprocessed frequency domain, the methodology enhances mode identification by refining the frequency content. Specifically, the methodology herein offers three key benefits. First, as can be seen in Figure 8-10, it mitigates the

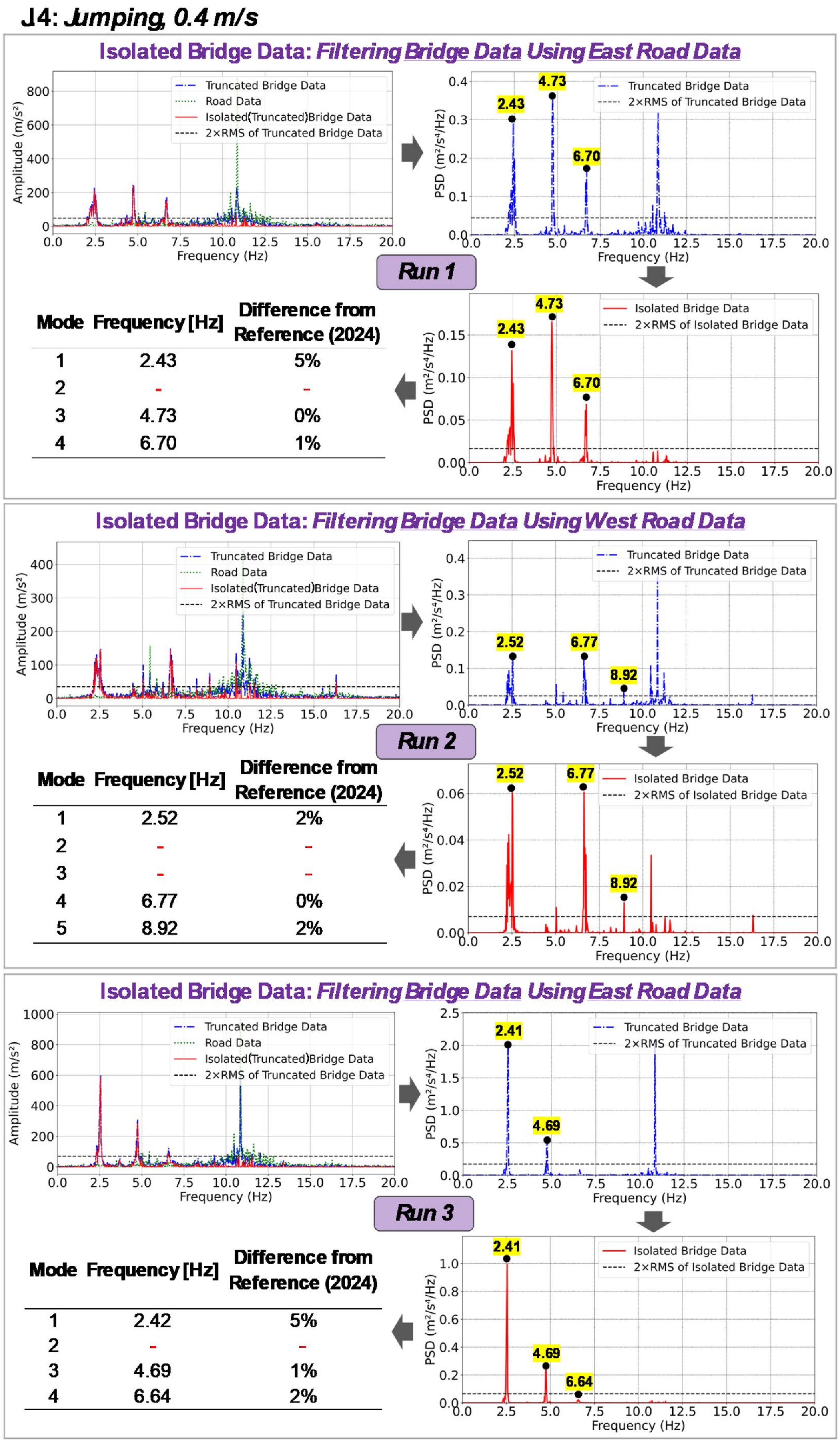


Figure 8. Test J.4 results: Drive-by mode identification results for three runs when the robot is at a slow speed and the bridge is under jumping excitation.

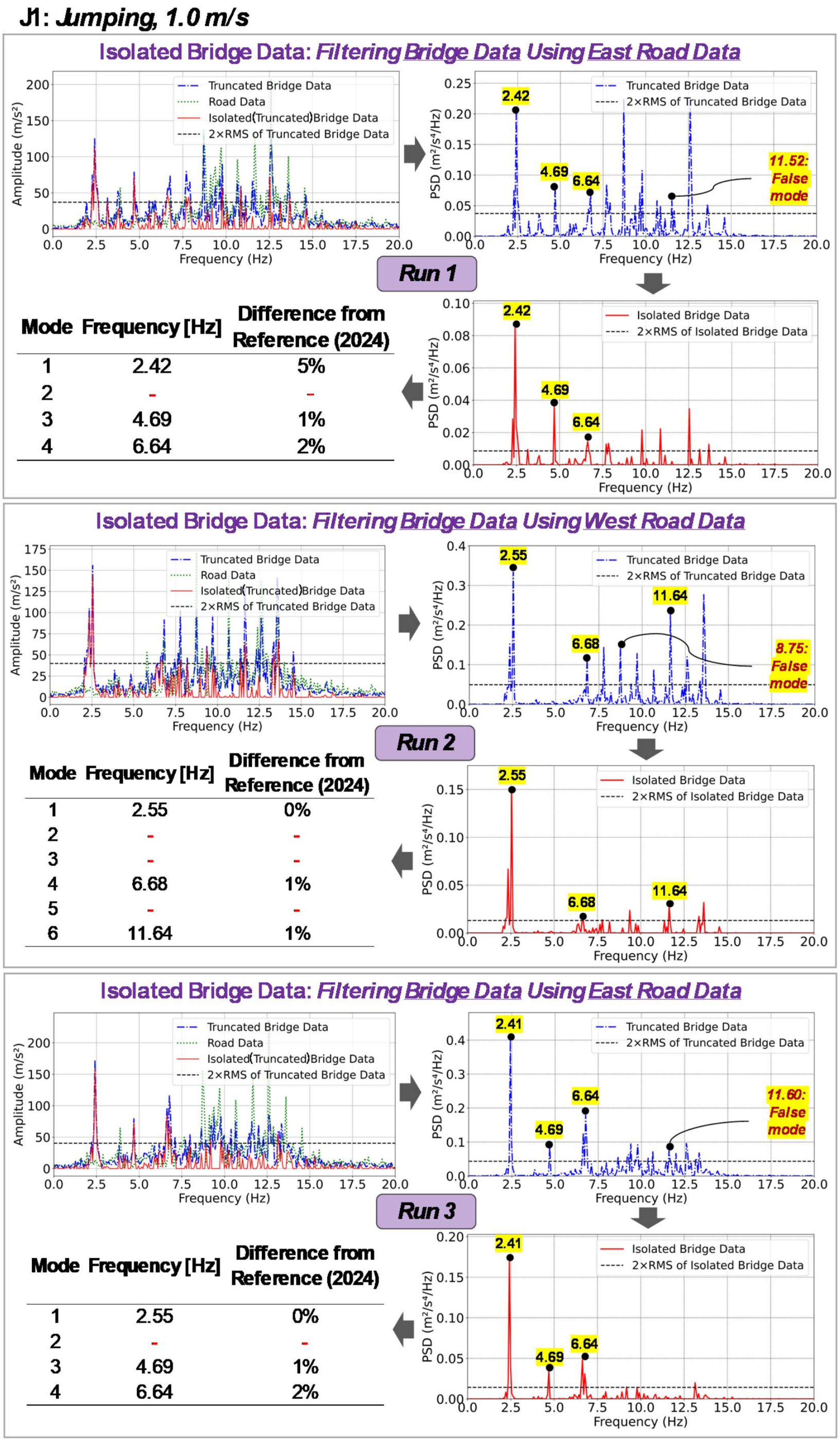


Figure 9. Test J.4 results: Drive-by mode identification results for three runs when the robot is at a fast speed and the bridge is under jumping excitation.

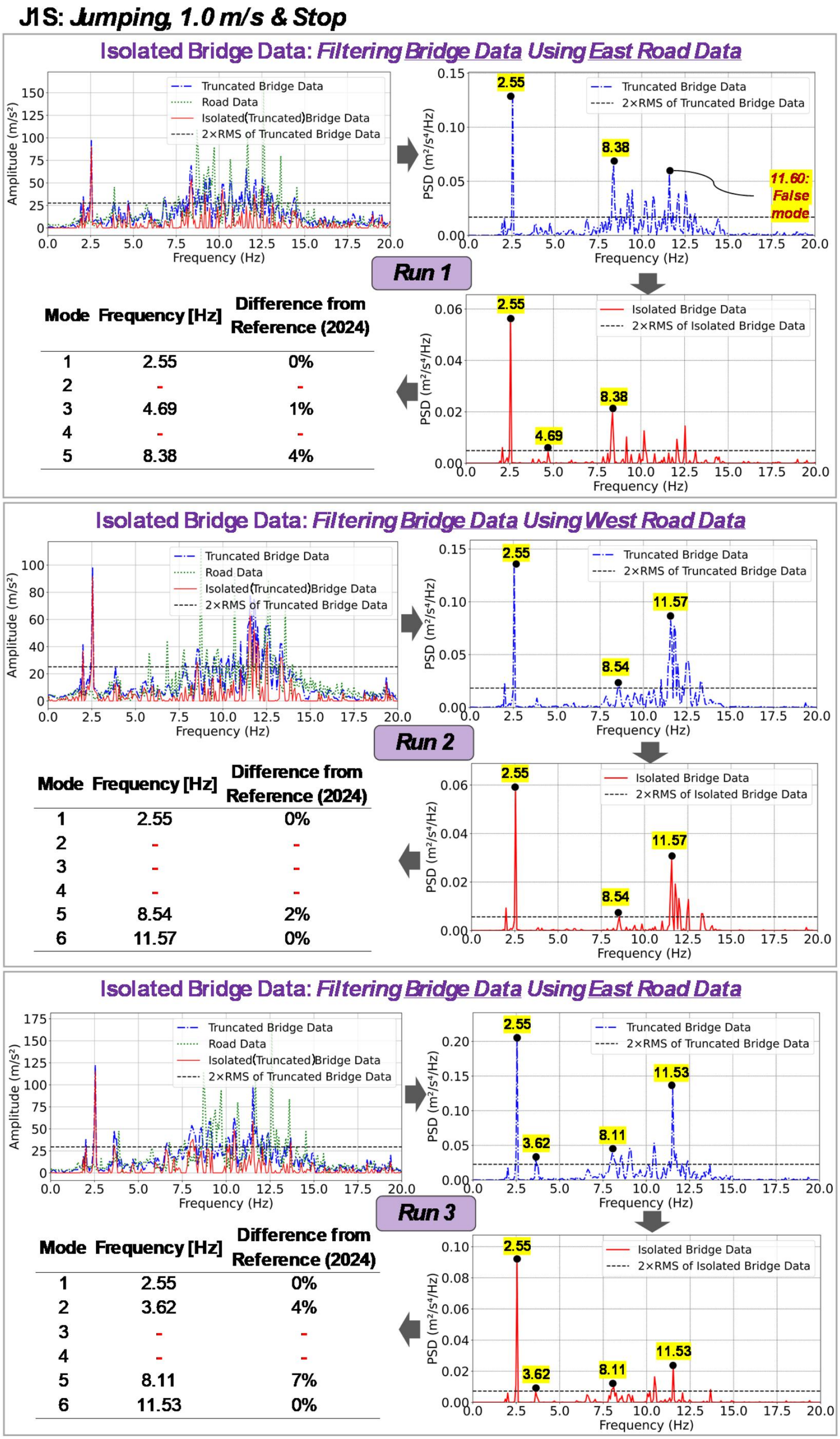


Figure 10. Test J.4 results: Drive-by mode identification results for three runs when the robot is at a fast speed and makes multiple stops (7), and the bridge is under jumping excitation.

influence of road roughness, vehicle-induced dynamics, and other contributory noises in the frequency domain, allowing true bridge mode peaks to stand out more clearly and improving the detection of subtler frequencies. Second, it prevents false mode identification, as seen in scenarios like J1-Run1–3 (Figure 9) and J1S-Run1 (Figure 10), where up to four incorrect mode peaks were observed. Third, it facilitates the identification of additional modes that were previously undetectable, such as Mode 2 in J1S-Run1 (Figure 10) and Mode 3 in J.4-Run3 (Figure 9).

Nevertheless, as can be observed in the figures, there are minor residuals left after applying the isolation methodology. These residuals are more pronounced for the J1 and J1S cases (fast and fast & stop) than the J.4 case (slow). Filtering the amplitude spectra of the bridge data using the road data (as shown in Eq. (5)) should have isolated the bridge response component. However, the persistence of these residuals suggests four possible contributing factors:

1. The road surface cannot be completely identical to the bridge surface due to its heterogeneity, potentially causing these residuals after the isolation methodology.
2. In J1S, the robot's speed varied between drive and stop intervals. Since the road data used for filtering was collected at a constant speed, applying it to the bridge data with varying speed contributed to the formation of residuals. As a result, the residuals in J1S are slightly more noticeable than those in J1.
3. Equations (1-2) ignore other potentially involved factors, such as the dynamic interactions between vehicle-road and vehicle-bridge, which arise from coupling effects caused by the vehicle's motion, including forces transmitted through the tires and the corresponding structural responses of the road and bridge to the moving load.
4. While the methodology assumes linear superposition, non-linear interactions, such as dynamic dependencies and higher-order harmonics, are likely to occur in reality, introducing complexities that cannot be fully captured or eliminated through simple filtering. This results in residuals when road data is used to filter bridge data, reflecting the unaccounted influence of these non-linear dynamics.

Accounting for these hypotheses, Equation (1) is revised and presented in equation:

$$H_B(f) = \mathcal{F}\left[H_b(f), H_r(f), H_v(f), H_s(f), H_{v-r}(f), H_{v-b}(f), H_n(f)\right] \tag{7}$$

where $H_{v-r}(f)$ represents the frequency response of vehicle-road interaction and $H_{v-b}(f)$ the vehicle-bridge interaction. The function $\mathcal{F}$ mathematically accounts for the combination and interaction of all the components contributing to the data measured from the bridge, $H_B(f)$, capturing both linear superpositions and nonlinear interactions that influence the collected total signal. The same revision can be applied to Eq. (2) without including the bridge-related component, $H_b(f)$.

Building on these revisions, future work should prioritize refining the paper's methodology to more effectively isolate the bridge response from other contributing factors while accounting for non-linear interactions and dynamic dependencies. In the isolation process, leveraging the data collected from the adjacent road can be an effective approach, like the methodology presented herein, to separate road-related influences from the bridge response. Also, collecting large sets of data will provide a better statistical characterization, which will also be explored in future work. Employing advanced signal processing techniques, such as variational mode decomposition (OBrien et al., 2017) and deep learning methods (Luleci et al., 2022), can significantly enhance the ability to capture and address these non-linear influences. These methodologies should involve rigorous experimental validation through controlled and real-world tests encompassing different bridge types, varied surface types, vehicle speeds, and excitation levels, which will provide critical insights, fostering further optimization and improving the robustness of this methodology herein or other similar approaches.

Another important avenue for future work is expanding the extracted modal parameters beyond frequencies to include mode shapes, which are crucial for localizing structural damage and understanding bridge dynamics. While the current setup identifies modal frequencies, mode shape extraction could be achieved by deploying multiple sensor-equipped UGVs along different trajectories or synchronizing drive-by passes for spatial interpolation. Additionally, addressing environmental influences, particularly temperature variations, is vital for reliable long-term monitoring. Temperature fluctuations can alter modal properties, potentially masking structural damage and necessitating compensation strategies. Future efforts should integrate temperature correction models, data normalization, or auxiliary environmental sensors on the UGV platform to enhance robustness. By refining response isolation, incorporating environmental compensation, and expanding extracted parameters, this filtering-based methodology can become a more comprehensive and practical solution for real-world drive-by bridge monitoring.

9. Multi-tiered bridge network reliability with CVs and robots

The adoption of CVs and robot-based systems for bridge assessment can offer a robust framework for bridge network reliability monitoring, as illustrated in Figure 11 and inspired by Prof Franpol's bridge network works, like in Figure 1. In the context of structural reliability, the reliability index β is a dimensionless measure of safety and can be defined with the well-known formulation:

$$\beta = \frac{\mu_c - \mu_d}{\sqrt{\sigma^2{}_c + \sigma^2{}_d}} \tag{8}$$

where μ_c is mean capacity, μ_d is mean demand, $\sigma^2{}_c$ is variance in capacity, and $\sigma^2{}_d$ variance in demand. β quantifies the safety margin between the bridge's capacity and the

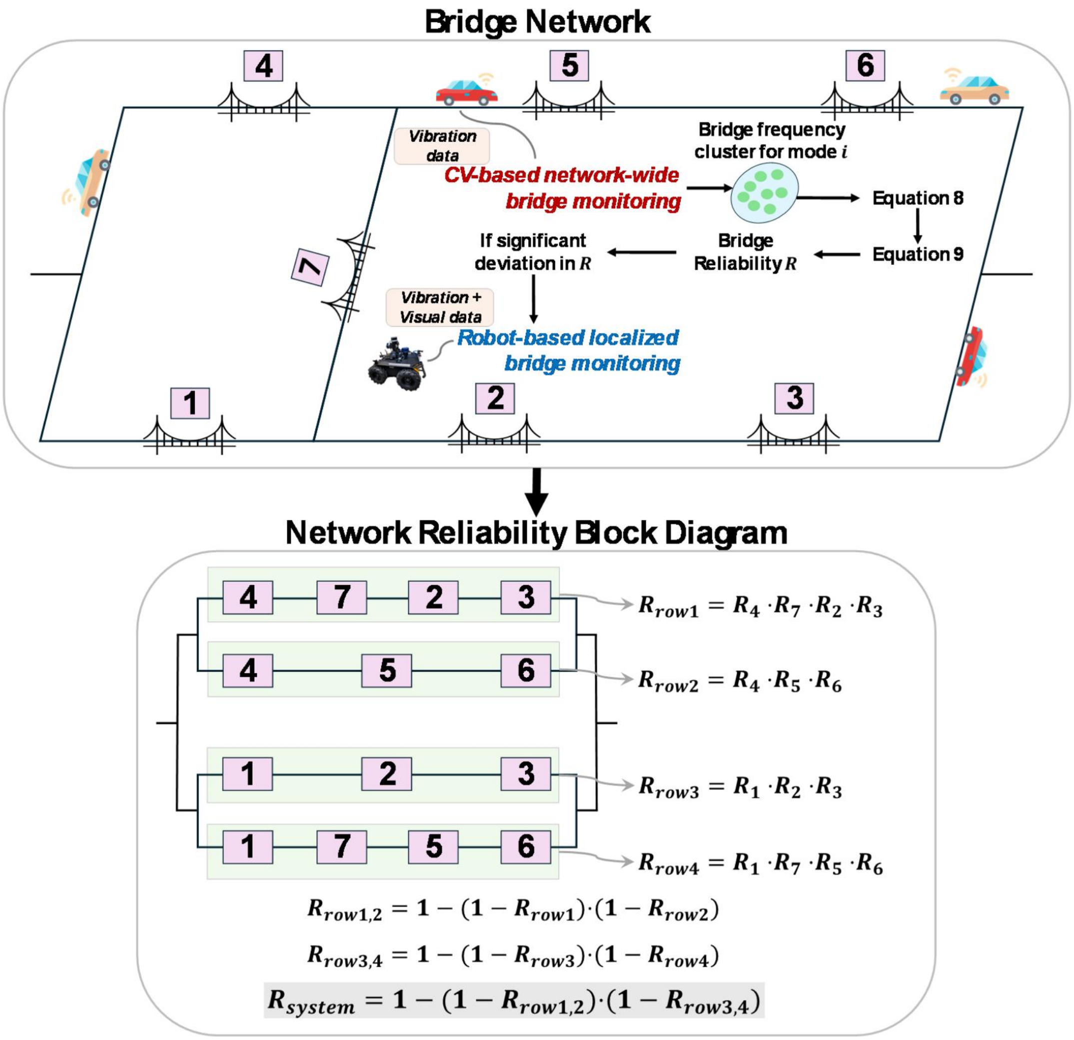


Figure 11. Multi-tiered framework for bridge network reliability monitoring using CVs and mobile robots.

imposed demand, and a higher β corresponds to a lower probability of failure P_f, which is the likelihood that the demand exceeds the capacity. P_f is related to the reliability index β through the cumulative distribution function of the standard normal distribution Φ:

$$P_f = 1 - \Phi(\beta) \tag{9}$$

where $\Phi(\beta)$ represents the reliability R, which is the probability that the safety margin is greater than zero.

In a conceptual scenario, a bridge mode i identified by n vehicle pass over a bridge produces *in* amount of bridge modes. The mean μ and variance σ of this bridge mode distribution represent the demand parameters μ_d and $\sigma^2{}_d$. With known capacity parameters μ_c and $\sigma^2{}_c$ from the established baseline distributions or other analytic approaches, the bridge reliability index β can be identified. When the bridge has a structural issue, the deviation in β could be even more pronounced. The authors' future work will also focus on the utilization of CV-based monitoring for network-level identification of structural changes that can be incorporated in the life cycle assessment of structures at the network level.

For each bridge, CVs facilitate the estimation of demand parameters by generating distributions of bridge frequency data across multiple vehicle passes. CVs essentially provide a near real-time picture of the demand imposed on the network, identifying potential anomalies or shifts that may indicate structural issues. The widespread deployment of CVs ensures systematic monitoring of all bridges, including those in remote areas, helping prioritize bridges for further assessment based on identified demand parameters. However, due to variability in vehicle dynamics, road conditions, noise in CV data, or more detailed assessment requirements, additional approaches might be often needed to refine the accuracy of reliability estimates for critical or high-priority structures.

Robots may complement CVs by addressing the limitations of demand parameter estimation and helping identify capacity parameters. Once CV-based monitoring identifies a potential hotspot or a bridge requiring further attention, robots are deployed for detailed assessments. Unlike CVs, robots operate under controlled conditions, ensuring repeatable and consistent data collection. Equipped with multi-modal sensors, robots' dual capability to capture both vibration data and visual data further enhances the accuracy of capacity parameter identification. For example, robots identify visible signs of deterioration, such as cracks, spalling, or surface wear, which can inform the baseline capacity and its variability while assisting in defining the capacity parameters. This localized and detailed data collection ensures that the capacity parameters reflect the actual structural state and reduces uncertainties in "reliability estimation." This can be achieved either by better calibrating structural models or some other type of formulation.

At the bridge network level, CVs continuously gather data to identify demand parameters for all bridges in the network. This data provides the foundation for calculating preliminary reliability indices for each bridge. Bridges with lower reliability indices, which may indicate potential structural issues, are flagged for further investigation. Robots are then deployed to these flagged locations for targeted assessments. By providing accurate capacity estimates and refining demand estimates through localized data collection, robots improve the reliability index calculations for these critical structures. This integrated approach has the potential to ensure that bridges with the greatest need for maintenance or intervention are prioritized, enabling efficient resource allocation. Advanced data analytics and centralized monitoring platforms can be used to scale this approach. Data from CVs can be aggregated and processed in near real-time to estimate reliability indices for each bridge. When robots are deployed, their data can update these indices with higher precision. This iterative process would allow for dynamic network monitoring to update reliability indices as new data becomes available continuously.

10. Conclusions

This study explored a practical and scalable methodology for indirect bridge monitoring using a mobile robot equipped with multi-modal sensors. It addressed challenges such as road roughness, vehicle dynamics, and other noises to isolate bridge responses by leveraging data from the adjacent roadways connecting the bridge for accurate mode identification. It further investigated varying driving speeds, drive-stop scenarios, and robot trajectories to evaluate the bridge mode detection conditions. The study's methodology was applied to a bridge for various drive-by monitoring scenarios under pedestrian jumping excitation, with the resulting bridge vibration modes analyzed and discussed extensively. The study's key conclusions are summarized as follows:

- The proposed filtering-based methodology effectively mitigates the influence of road roughness, vehicle dynamics, and external noise, enhancing the clarity and accuracy of bridge mode identification. As a result, this approach allowed for the successful identification of up to the first six bridge modes across nine test scenarios, with an average variation of only 2% from the reference test.
- Among the test scenarios, the drive-stop case captured the highest number of modes due to increased data volume and clarity, while the slow-driving scenario provided the clearest mode peaks. Stopping intervals improved overall data quality, whereas fast speeds reduced peak clarity, potentially leading to incorrect mode selection. The optimal approach for capturing more distinctive bridge modes is hypothesized to be a drive-stop strategy at a slower speed.
- Driving on the sides or in the middle of the bridge did not significantly affect mode identification results, although torsional modes were generally missing in middle runs. Both torsional and bending modes appeared equally in runs along the south and north sides. However, these findings may vary depending on the bridge's flexibility and geometry, as stiffer bridges with localized vibrations may require specific trajectories for mode detection, while more flexible bridges allow for easier detection across trajectories. Conducting runs along all sides of the bridge is recommended to ensure comprehensive mode identification.
- The minor residuals after applying the isolation methodology underscore limitations arising from road surface heterogeneity, vehicle-road/vehicle-bridge interactions, and non-linear dynamics, which are not fully addressed by the methodology herein. Future refinements, validated through rigorous real-world testing, should incorporate advanced signal processing techniques and account for these non-linear effects to enhance the accuracy and robustness of bridge response isolation.
- Future work will focus on refining the methodology to better isolate bridge responses by addressing non-linear interactions and leveraging data from adjacent roads. Larger datasets and advanced techniques like variational mode decomposition and deep learning will be considered to enhance analysis. Validation across varied bridge types, surface conditions, and vehicle speeds will optimize and strengthen the approach to support network-level life cycle analysis and evaluation.
- The integration of CVs and robots creates a multi-tiered framework for bridge network reliability monitoring, leveraging their complementary strengths to maximize efficiency and accuracy. CVs excel at network-level assessments, providing continuous estimations of demand parameters across the network, while robots deliver higher precision through element-level evaluations. With their dual capability for real-time bridge mode identification and visual data analysis, robots can enhance demand estimations and inform capacity parameters through detailed, localized assessments. This combined approach potentially enables accurate reliability index calculations, facilitates rapid decision-making, supports early detection of bridge condition changes, and promotes proactive infrastructure management with optimized resource allocation.

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Availability of data and material

Some or all used models, codes, and detailed results are available from the authors of this paper upon request.

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Appendix

Figure A1. Frequency domains of the data collected *via* robot on different roads and speeds.

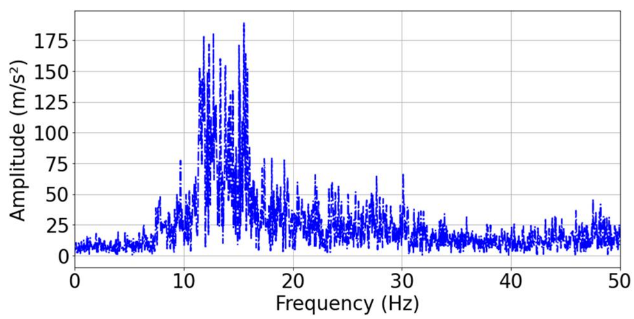

Figure A2. Frequency domain of the robot after tapping test for 25 s on the robot itself.