Laboratory validation of a crowdsourced drive-by bridge monitoring method

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Abstract. This paper presents a novel approach to the drive-by Structural Health Monitoring (SHM) of bridges based on crowdsourced data collected from multiple vehicle passages. The methodology is experimentally validated on a laboratory-scale bridge model designed to replicate the dynamic behaviour of real bridge structures, exhibiting representative natural frequencies and mode shapes. Acceleration data were acquired using smartphones mounted on a specially adapted vehicle traversing the bridge under varying conditions, including different speeds, directions, and lateral positions. Multiple crossings were conducted to simulate a crowdsourcing scenario, where independent vehicle measurements contribute to a shared monitoring database. This experimental setup enabled the evaluation of how data aggregation from numerous runs can enhance the robustness and accuracy of the drive-by monitoring technique. The collected acceleration signals were processed in MATLAB to extract the bridge's key dynamic parameters. The analysis focused on estimating natural frequencies and identifying mode shapes based on the aggregated datasets. The results were compared with reference measurements obtained from high-precision accelerometers permanently installed on the bridge model. The identified parameters showed only minor deviations—typically within a few percent—from the reference values, confirming the reliability of the proposed approach. Furthermore, combining data from multiple vehicle passages reduced measurement variability and improved the stability of the identified dynamic characteristics. The findings demonstrate the feasibility and potential of using crowdsourced data for drive-by bridge monitoring with widely available mobile sensors. By leveraging repeated measurements from multiple independent crossings, the study highlights a scalable, low-cost, and non-invasive solution for continuous bridge health assessment. This approach paves the way toward practical implementation of large-scale SHM systems capable of exploiting existing traffic as a dynamic sensing network.

Keywords: Drive-by Structural Health Monitoring (SHM), bridge dynamics, crowdsourced sensing, smartphone accelerometers, natural frequency and mode shape identification

1. Introduction

Bridges are long-lived structures, yet a significant portion of existing bridge stock currently operates beyond its originally intended service life while being exposed to increasing traffic demands and environmental effects [1]. Material aging, cumulative fatigue, corrosion, and temperature variations progressively influence structural stiffness and dynamic behaviour [2]. Consequently, infrastructure managers face the challenge of ensuring safety and serviceability across extensive bridge networks, often under limited financial and operational resources [3]. These conditions have intensified the need for monitoring strategies that are not only reliable and sensitive to structural degradation, but also economically scalable. Conventional Structural Health Monitoring (SHM) systems typically rely on permanently installed sensors distributed along the structure [4]. Such systems provide highly accurate modal parameters, including natural frequencies and mode shapes, which are widely recognized as sensitive indicators of structural condition. However, installation costs, maintenance requirements, power supply constraints, and data management complexity limit their large-scale deployment, particularly for short- and medium-span bridges [5]. To address these limitations, drive-by SHM [6] has emerged as an alternative approach in which vibration data are collected from sensors mounted on moving vehicles. Instead of directly instrumenting the bridge, the dynamic interaction between the vehicle and the structure is exploited to extract information about structural properties. Numerous numerical such [7]–[9] and experimental studies such [10]–[12] have demonstrated that bridge natural frequencies can be identified from vehicle-mounted accelerometers. The approach is attractive because it minimizes infrastructure intervention and allows repeated measurements without interrupting traffic. Recent advances in mobile sensing technologies have further expanded this concept. Modern smartphones, equipped with MEMS accelerometers and wireless communication capabilities, have been investigated [13], [14] as low-cost sensing platforms for vibration-based monitoring. Previous studies [11], [15], [16] have shown that smartphone measurements can capture modal features relevant for structural identification, opening the possibility of distributed monitoring without dedicated sensor installation. Building upon this idea, crowdsourced monitoring frameworks have been proposed in which ordinary traffic effectively functions as a distributed sensing network. By aggregating vibration data from multiple independent vehicle trips, researchers aim to enhance robustness and spatial coverage while maintaining low implementation costs. Matarazzo et al. [17] suggested that crowdsourcing-based monitoring strategies could potentially extend bridge service life by up to 30% without additional infrastructure investment. Other studies such [18]–[20] have demonstrated the feasibility of extracting modal properties from aggregated smartphone data and have explored preprocessing, data fusion, and quality control strategies. Despite these promising developments, several challenges remain. Vehicle-mounted measurements inherently contain contributions from vehicle dynamics, suspension characteristics, road surface irregularities, operational variability, and measurement noise. Data heterogeneity—stemming from differences in vehicles, sensor placement, speed, and environmental conditions—introduces additional uncertainty. Previous research has shown that aggregation of multiple trips improves identification stability, but the improvement may saturate beyond a certain sample size, and controlled measurements generally outperform fully uncontrolled datasets [19]. However, the quantitative relationship between the number of aggregated crossings, traffic configuration, and the convergence behaviour of both natural frequencies and reconstructed mode shapes remains insufficiently characterized. These findings underline the importance of systematic filtering, statistical validation, and physically consistent interpretation of aggregated modal parameters. In this context, the present study proposes a deterministic crowdsourced drive-by monitoring framework for bridge model identification and mode shape reconstruction under constant vehicle speed. Unlike probabilistic crowdsourcing approaches that rely on GPS-based spatial segmentation, the proposed method preserves deterministic time-to-space mapping by exploiting known constant vehicle velocity. Each vehicle crossing is treated as an independent spatial realization of the modal amplitude distribution, while crowdsourcing is introduced as a statistical convergence layer applied after deterministic reconstruction. In this way, random components related to vehicle–bridge interaction and measurement noise are progressively suppressed through aggregation, while maintaining the physical interpretability of the reconstructed mode shapes. Particular emphasis is placed on evaluating (i) the robustness of frequency identification under different traffic configurations, (ii) the statistical convergence of modal parameters as the number of aggregated crossings increases, and (iii) the saturation behaviour of reconstruction accuracy quantified through the Modal Assurance Criterion (MAC). The proposed framework is experimentally validated on a laboratory-scale bridge model under controlled yet heterogeneous traffic scenarios. Attention is given to the statistical convergence behaviour of reconstructed modal amplitudes as the number of aggregated crossings increases. The analysis further investigates how single-, two-, and three-vehicle configurations influence the rate of convergence while assessing whether the final identified modal properties remain unbiased with respect to reference OMA values. The remainder of the paper is structured as follows. Section 2 presents the proposed deterministic crowdsourced drive-by methodology. Section 3 describes the experimental case study and reference modal characterization. Section 4 presents the identification results and convergence analysis and discusses the implications and limitations of the approach. Finally, Section 5 summarizes the main findings and outlines directions for future research.

2. Crowdsourced deterministic drive by bridge methodology for modal identification

The proposed framework is based on a deterministic interpretation of drive-by bridge monitoring under constant vehicle speed. In contrast to probabilistic crowdsourcing approaches that rely on GPS-based spatial segmentation and statistical alignment of measurements, the present method preserves physical consistency by exploiting known vehicle kinematics. The central idea is that, if the vehicle travels across the bridge at constant velocity, the measured time-domain signal can be deterministically mapped into spatial coordinates. This eliminates the need for probabilistic spatial alignment and enables physically consistent reconstruction of modal amplitude distributions along the bridge span.

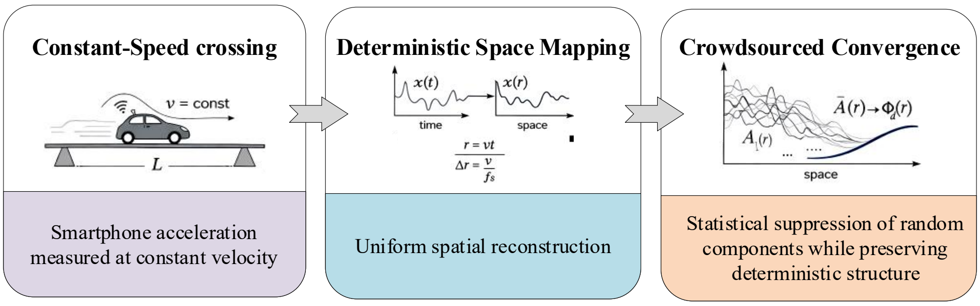

Fig. 1. Deterministic crowdsourced drive-by SHM framework

Let the vehicle velocity be constant and equal to v. The longitudinal coordinate along the bridge span of length Lis then related to time through

$$r(t) = vt, r \in [0, L] \quad (1)$$

This simple kinematic relationship establishes a one-to-one mapping between time and space. Consequently, the measured vertical acceleration signal x(t) can be re-parameterized as a spatial signal x(r). The spatial sampling resolution is governed by the ratio v/f_s, where f_s is the sampling frequency. Importantly, this resolution remains constant along the span, ensuring uniform spatial discretization and eliminating the need for GPS-based position correction. From a structural dynamics' perspective, the measured acceleration may be represented as a modal superposition of the form

$$x(r,t) = \sum_{d=1}^{D} \Phi_d(r)\, q_d(t) + \varepsilon(t), \quad (2)$$

where $\Phi_d(r)$denotes the d-th mode shape, $q_d(t)$ is the associated modal coordinate, and ε(t) accounts for vehicle-induced disturbances and measurement noise. For lightly damped bridges under ambient excitation, modal coordinates can be approximated as narrowband harmonic processes centered around the natural frequency f_d. Substituting the kinematic relation t=r/v reveals that structural frequencies manifest as spatial oscillations along the bridge when the vehicle speed is constant. Thus, the temporal vibration content of the bridge is encoded as a spatial modulation observed by the moving sensor. Modal isolation is performed through deterministic narrowband filtering around the identified natural frequency. Rather than relying on probabilistic ridge extraction in the time–frequency domain, the method directly extracts the analytic signal using the Hilbert transform and computes its amplitude envelope. For each vehicle crossing i, this procedure produces a spatial modal amplitude estimate $A_i(r)$. Each crossing therefore yields an independent spatial realization of the same underlying modal shape. However, the amplitude obtained from a single passage does not represent the pure structural mode. It can be interpreted as

$$A_i(r) = \Phi_d(r) + \epsilon_i(r) \tag{3}$$

where $\epsilon_i(r)$ includes contributions from vehicle–bridge interaction, suspension dynamics, road roughness, and sensor noise. These components vary from one crossing to another and can be considered stochastic perturbations superimposed on the deterministic structural response. The crowdsourcing mechanism is introduced at this stage as a statistical convergence layer. If the disturbance terms $\epsilon_i(r)$ are weakly correlated and approximately zero-mean across independent crossings, aggregation of N realizations lead to variance reduction proportional to $1/N$. The aggregated estimator:

$$\bar{A}(r) = \frac{1}{N}\sum_{i=1}^{N} A_i\,(r), \tag{4}$$

converges in expectation toward the true modal shape $\Phi_d(r)$as Nincreases. In practical terms, each additional crossing reduces random variability while preserving the deterministic spatial structure imposed by constant vehicle speed. Thus, repeated vehicle passages improve the signal-to-noise ratio without altering the underlying physical reconstruction. This theoretical variance reduction explains the experimentally observed decrease in frequency error and the gradual stabilization of MAC values with increasing aggregation. For improved robustness against outliers or non-Gaussian disturbances, median-based aggregation may be employed instead of arithmetic averaging. A key theoretical distinction of the proposed framework is that crowdsourcing does not replace deterministic identification. Frequency estimation and spatial reconstruction are performed at the level of individual crossings. Statistical aggregation is applied only afterward to enhance stability and suppress random components. This separation ensures that physical interpretability is retained while statistical convergence is used solely to improve robustness. Since mobile sensing does not provide absolute amplitude scaling, the final reconstructed modal shape is normalized by its maximum absolute value and smoothed using spline interpolation to obtain a continuous spatial representation suitable for comparison with reference modal data.

3. Case study

The proposed deterministic crowdsourced drive-by SHM methodology was experimentally validated using a laboratory-scale bridge model with well-defined boundary conditions and reproducible dynamic behaviour. The controlled environment enabled systematic evaluation of the framework while preserving realistic structural dynamics, including clearly identifiable natural frequencies and mode shapes. Acceleration measurements were collected using smartphones mounted inside test vehicles serving as mobile sensing platforms. Each vehicle crossing was treated as an independent realization of the coupled vehicle–bridge system. Repeated passages were performed to simulate a controlled crowdsourced monitoring scenario, in which multiple independent measurements are aggregated to enhance statistical stability and modal identification robustness.

3.1. Description of the structure

The experimental campaign was conducted on a purpose-built laboratory bridge model located at University College Dublin (UCD). The structure was specifically designed for research on drive-by monitoring techniques, allowing controlled testing under repeatable boundary and loading conditions. The bridge consists of a 5 mm thick steel plate with a width of 600 mm. To increase bending stiffness and achieve representative flexural behaviour, six longitudinal steel angle sections (20 × 20 × 3 mm)

are attached beneath the plate. The material properties correspond to structural steel with a Young's modulus of 210 GPa. The span length between supports is 2000 mm. Simply supported boundary conditions are approximated using a steel shaft supported by pillow block bearings, allowing free rotational movement at both ends. The bearing assemblies are mounted on a custom-designed 3D-printed support frame to ensure geometric stability and repeatability during testing. Although reduced in scale, the model was dimensioned to reproduce the dynamic characteristics of a typical 25 m reinforced concrete beam-and-slab bridge. Geometric and stiffness parameters were selected to preserve dynamic similitude, particularly with respect to fundamental vibration behaviour.
The experimentally determined first natural frequency of the model was 8.8 Hz, providing a clearly identifiable modal response suitable for drive-by identification and validation. The well-controlled laboratory conditions and known structural properties make this model particularly suitable for assessing repeatability, robustness, and statistical convergence of the proposed methodology.

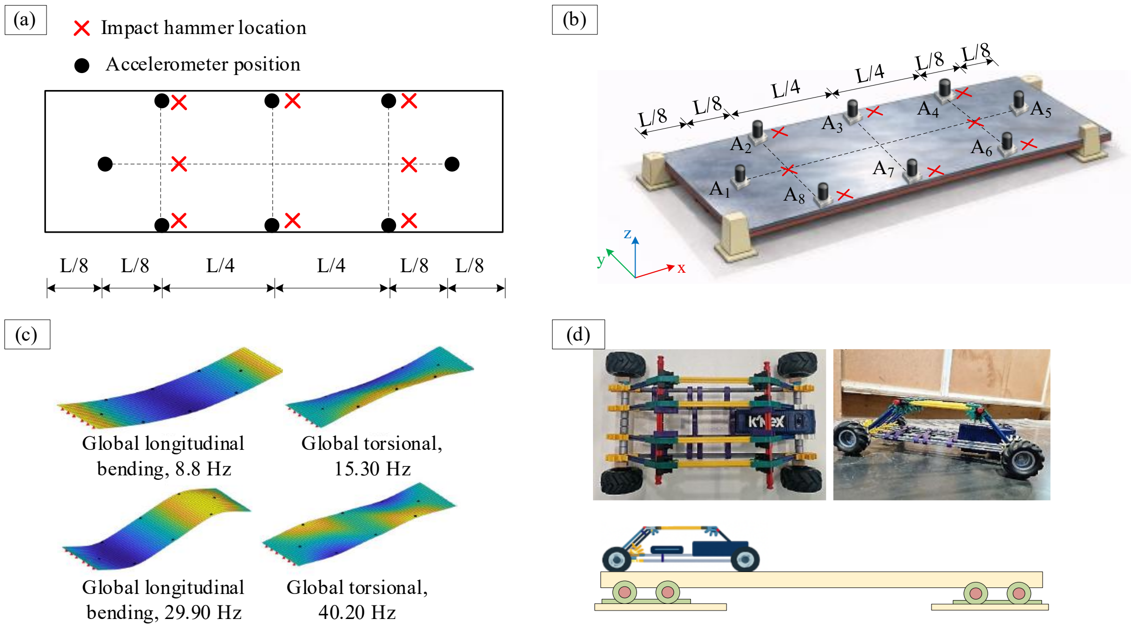

Fig. 1. Experimental framework for validation of the proposed monitoring methodology: (a) sensor layout and hammer impact locations; (b) three-dimensional view of the laboratory bridge model; (c) reconstructed OMA mode shapes; (d) vehicle model for drive-by measurements.

3.2. Crowdsourced based drive-by bridge monitoring

Drive-by monitoring was performed using three passenger vehicle models equipped with smartphones acting as mobile sensing units. Smartphones recorded tri-axial acceleration at a sampling frequency of 100 Hz. GPS data (up to 10 Hz) were collected only for validation purposes and were not used for spatial reconstruction, in accordance with the deterministic time-to-space mapping framework. During each crossing, vehicles were operated at predefined constant speeds to satisfy the kinematic relation: $r(t) = vt$. This ensured uniform spatial discretization of the measured signals. In total, approximately 500 drive-by records were collected. The resulting dataset represents a controlled yet heterogeneous crowdsourcing scenario in which repeated independent realizations contribute to a shared monitoring database.

3.3.1 Experimental Configuration

To evaluate robustness under increasing interaction complexity, three traffic configurations were considered: (1) Single-vehicle crossing – one vehicle traversed the bridge at constant speed; (2) two-vehicle crossing (opposite directions) – two vehicles simultaneously crossed the bridge from opposite ends; (3) Three-vehicle configuration – two vehicles entered from opposite ends while a third vehicle started from mid-span. These configurations progressively increased the level of dynamic interaction and excitation complexity, approximating realistic traffic scenarios. Each crossing was treated as an independent dataset within the aggregated monitoring framework.

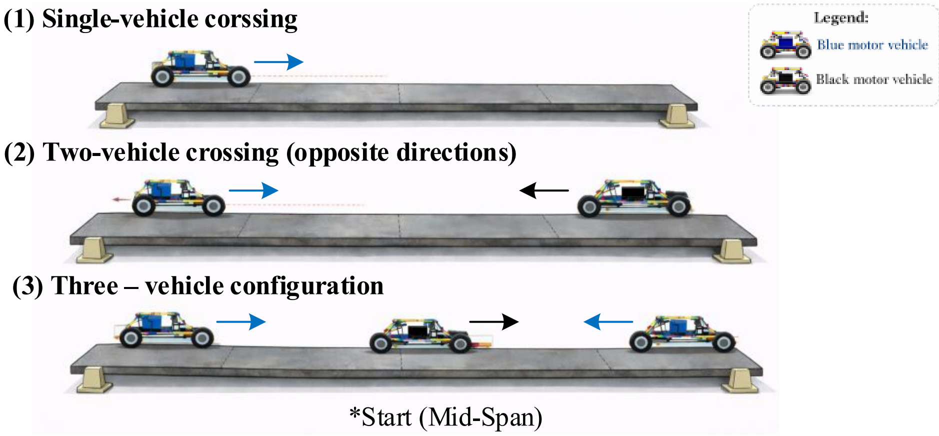

Fig. 2. Vehicle crossing configurations considered in the experimental campaign

3.3.2 Signal processing and modal identification

Acceleration signals from each crossing were processed in MATLAB following the deterministic methodology described previously: (1) signal conditioning (detrending and band-pass filtering), (2) time-to-space transformation using constant speed, (3) Synchrosqueezed Wavelet Transform (SSWT), (4) spatial segmentation and modal energy estimation, (5) aggregation across multiple independent runs. Rather than extracting modal frequencies from individual crossings, frequency identification was based on aggregated spectral information derived from multiple passages. This reduces sensitivity to vehicle-specific dynamics and measurement noise. For each identified modal frequency f_d, the spatial modal amplitude was estimated as:

$$A_d(s_m) = \sqrt{\frac{1}{N_m} \sum_{r \in s_m} |T_x(f_d, r)|^2} \quad (5)$$

where $T_x(f_d, r)$ denotes the SSWT coefficient at frequency f_d and spatial coordinate r, and s_m represents the spatial segment. This procedure allows reconstruction of the absolute value of the vertical mode shape.

3.3.3 Effect of data aggregation

The influence of increasing the number of crossings was evaluated by analysing the convergence behaviour of identified modal frequencies and reconstructed mode shapes. Statistical dispersion decreased systematically as additional runs were included in the aggregation process, demonstrating the stabilizing effect of crowdsourced data fusion. The results confirm that aggregation acts as a variance-reduction mechanism, improving signal-to-noise ratio and promoting statistical convergence of both frequency estimates and spatial modal reconstructions. Even under multi-vehicle configurations, repeated independent passages enhanced robustness without introducing systematic bias relative to the OMA reference.

4. Case study

4.1 Robustness of frequency identification

The robustness of the identified natural frequencies is illustrated in Fig. 4 through the distribution of results obtained from aggregated drive-by measurements. Across all traffic configurations, the identified frequencies remain closely aligned with the OMA reference values.

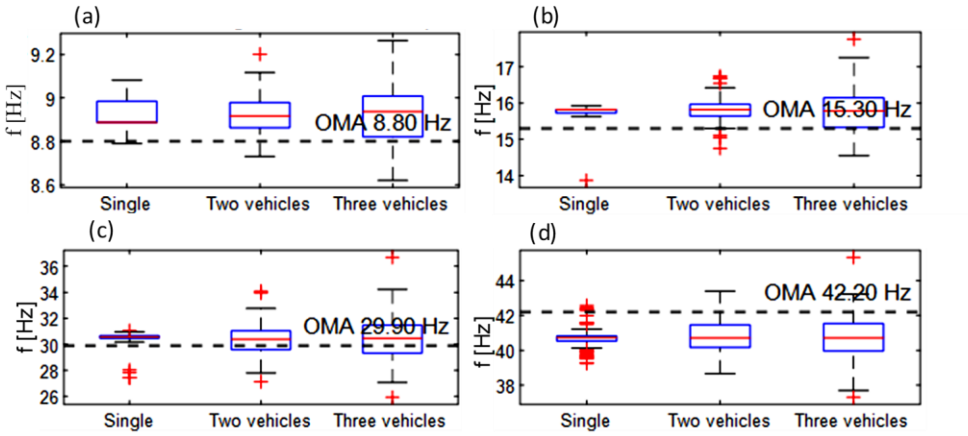

Fig. 3. Distribution of identified frequencies based on the different number of the single vehicle passing

The dominant bending mode shows minimal dispersion and stable median values, even when the number of crossings is limited. This indicates that frequency identification is inherently robust and only weakly influenced by individual vehicle–bridge interaction effects. Higher modes exhibit greater variability and occasional outliers, particularly under more complex traffic conditions. This increased spread reflects their higher sensitivity to excitation level and measurement noise. However, despite the larger dispersion, the median values remain consistently close to the OMA references, demonstrating that the method provides unbiased frequency estimates when sufficient data are available.

4.2. Effect of data aggregation

The influence of data aggregation is illustrated in Fig. 4. and Fig. 5. through the evolution of frequency errors and reconstructed mode shapes as the number of aggregated crossings (N) increases.

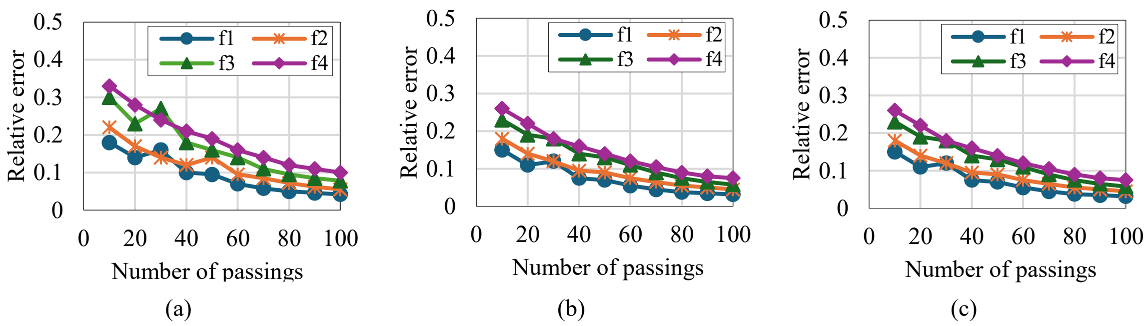

Fig. 4. Relative error of the identified modal frequencies as a function of the number of single-vehicle passages. Each curve corresponds to a different vibration mode.

As shown in Fig. 4., the relative error generally decreases for all modes as more crossings are included. The most pronounced improvement occurs at small sample sizes, where each additional crossing significantly enhances estimation accuracy. Although minor fluctuations are visible, particularly in the early aggregation stage, the overall trend is clearly convergent. Beyond approximately 60–70 aggregated crossings, the reduction in error becomes gradual, indicating that the results are approaching statistical saturation. This confirms that aggregation reduces variability and stabilizes the identified frequencies.

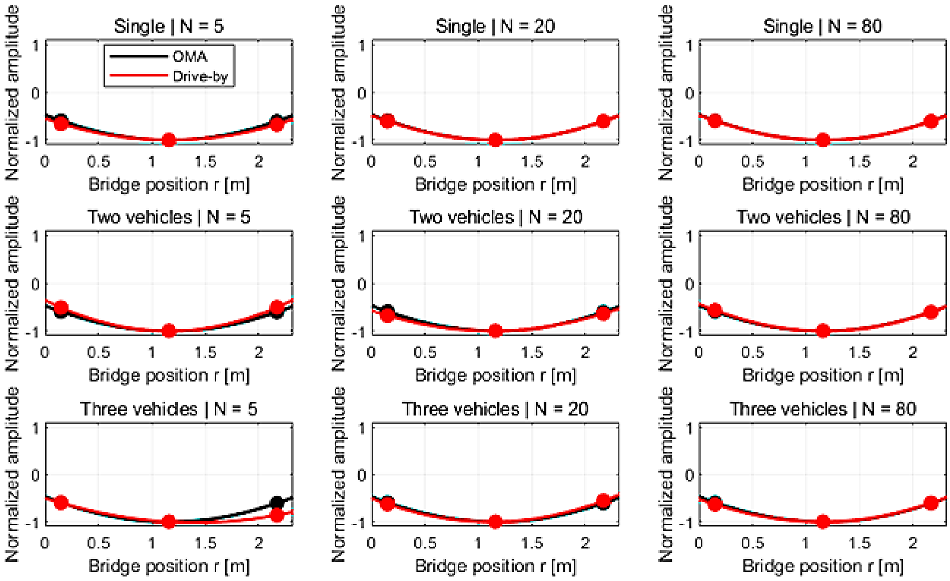

Fig. 5. Identified mode shapes for different number of vehicle passing and different vehicles configurations

A similar behaviour is observed for the reconstructed mode shapes (Fig. 5.). For small N (e.g., N = 5), visible deviations from the reference OMA shape remain. With increasing N (N = 20 and N = 80), the reconstructed shapes become smoother and progressively closer to the reference distribution. This trend is consistent across traffic configurations and shows that aggregation suppresses random fluctuations in the spatial response.

4.3. Influence of traffic configuration

Traffic configuration primarily influences the rate of convergence rather than the final identified modal properties. As shown in Fig. 6., the single-vehicle case requires a larger number of crossings to reach stabilization, whereas two- and three-vehicle configurations exhibit faster convergence due to increased excitation energy and improved signal-to-noise ratio. Despite these differences in convergence speed, the final frequency estimates and MAC saturation levels remain comparable across configurations, confirming that the method is robust to traffic complexity when sufficient data are aggregated.

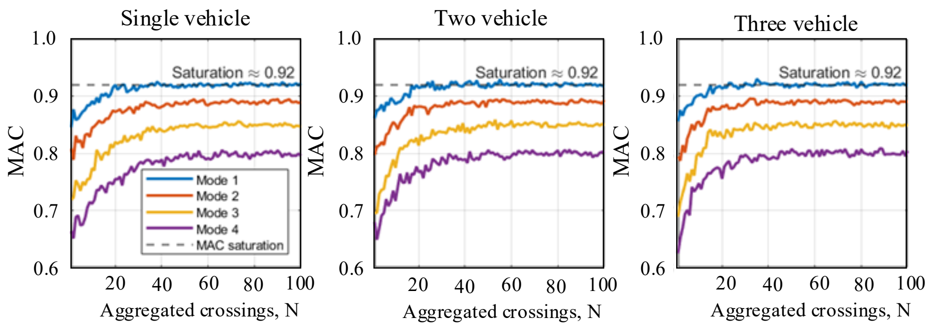

Fig. 6. Influence of traffic configurations and aggregation on identified mode shapes and their MAC factors

Fig. 6. further illustrates the evolution of the MAC values for the first four modes. The first bending mode reaches a saturation level of approximately 0.92 across all configurations, with multi-vehicle scenarios achieving stabilization at smaller numbers of crossings. Higher modes exhibit lower saturation levels and slightly slower convergence, with the second mode stabilizing close to 0.90 and the third mode converging toward approximately 0.80–0.85. These differences reflect reduced excitation efficiency and increased sensitivity to noise and spatial complexity in higher-order modes. Nevertheless, the overall convergence behaviour is consistent, demonstrating that statistical aggregation effectively improves modal shape reconstruction regardless of traffic configuration.

5. Conclusion

This study presented a deterministic crowdsourced drive-by framework for bridge frequency identification and mode shape reconstruction under constant vehicle speed. The methodology preserves physical consistency through direct time-to-space mapping, while aggregation of independent crossings serves to suppress random disturbances and improve the signal-to-noise ratio. Experimental validation on a laboratory-scale bridge model showed that frequency estimates stabilize rapidly with increasing numbers of crossings, converging toward the reference OMA values. Mode shape reconstruction exhibited a more gradual but consistent convergence pattern, with progressively increasing and saturating MAC values confirming statistical stabilization of spatial modal amplitudes. These findings demonstrate that repeated crossings primarily act as a variance-reduction mechanism, while the deterministic spatial reconstruction of the structural response remains physically interpretable. The framework-maintained robustness under multi-vehicle configurations, indicating that increased traffic complexity mainly affects the rate of convergence rather than the final identified modal properties. Future work will extend the approach to variable vehicle speed conditions, requiring adaptive time-to-space mapping based on continuous vehicle position estimation. This development will enable practical implementation under realistic traffic scenarios where strictly constant speed cannot be ensured.

Acknowledgements

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No [101151734].

References

F. Research and innovation in bridge maintenance, inspection and monitoring - A European perspective based on the Transport Research and Innovation Monitoring and Information System (TRIMIS). 2019; . https://doi.org/10.2760/719505.

[2] Giordano P.F.,Quqa S.,Limongelli M.P. The value of monitoring a structural health monitoring system. Struct. Saf. 2023; 100; 102280. https://doi.org/10.1016/j.strusafe.2022.102280.

[3] Marcheggiani L.,Clementi F.,Formisano A. Static and dynamic testing of highway bridges: a best practice example. J. Civ. Struct. Heal. Monit. 2020; 10; 43–56. https://doi.org/10.1007/s13349-019-00368-1.

[4] Chen H.-P. Structural health monitoring of large civil engineering structures. 1st editio, John Wiley and Sons Inc., Oxford, 2018; .

[5] Yu X.,Fu Y.,Li J.,Mao J.,Hoang T.,Wang H. Recent advances in wireless sensor networks for structural health monitoring of civil infrastructure. J. Infrastruct. Intell. Resil. 2024; 3; 100066. https://doi.org/10.1016/j.iintel.2023.100066.

[6] Yang Y.-B.,Lin C.W.,Yau J.D. Extracting bridge frequencies from the dynamic response of a passing vehicle. J. Sound Vib. 2004; 272; 471–493. https://doi.org/10.1016/S0022-460X(03)00378-X.

[7] Yang Y.B.,Lin C.W. Vehicle–bridge interaction dynamics and potential applications. J. Sound Vib. 2005; 284; 205–226. https://doi.org/10.1016/j.jsv.2004.06.032.

[8] Yang Y.B.,Yang J.P. State-of-the-Art Review on Modal Identification and Damage Detection of Bridges by Moving Test Vehicles. Int. J. Struct. Stab. Dyn. 2018; 18; 1850025. https://doi.org/10.1142/S0219455418500256.

[9] Corbally R.,Malekjafarian A. Bridge damage detection using operating deflection shape ratios obtained from a passing vehicle. J. Sound Vib. 2022; 537; 117225. https://doi.org/10.1016/j.jsv.2022.117225.

[10] Feng M.,Fukuda Y.,Mizuta M.,Ozer E. Citizen Sensors for SHM: Use of Accelerometer Data from Smartphones. Sensors 2015; 15; 2980–2998. https://doi.org/10.3390/s150202980.

[11] McSweeney N.,Ghiasi R.,Malekjafarian A.,Ozer E. Extracting Bridge Modal Frequencies Using Stationary Versus Drive-By Modes of Smartphone Measurements. Infrastructures 2024; 9; 218. https://doi.org/10.3390/infrastructures9120218.

[12] Castellanos-Toro S.,Marmolejo M.,Marulanda J.,Cruz A.,Thomson P. Frequencies and damping ratios of bridges through Operational Modal Analysis using smartphones. Constr. Build. Mater. 2018; 188; 490–504. https://doi.org/10.1016/j.conbuildmat.2018.08.089.

[13] Figueiredo E.,Moldovan I.,Alves P.,Rebelo H.,Souza L. Smartphone Application for Structural Health

Monitoring of Bridges. Sensors 2022; 22; 8483. https://doi.org/10.3390/s22218483.
[14] Ozer E.,Kromanis R. Smartphone Prospects in Bridge Structural Health Monitoring, a Literature Review. Sensors 2024; 24; https://doi.org/10.3390/s24113287.
[15] Shirzad-Ghaleroudkhani N.,Gül M. An Enhanced Inverse Filtering Methodology for Drive-By Frequency Identification of Bridges Using Smartphones in Real-Life Conditions. Smart Cities 2021; 4; 499–513. https://doi.org/10.3390/smartcities4020026.
[16] SS E.,L C.,SN P.,TJ. M. Wavelet Platform for Crowdsensed Modal Identification of Bridges. 2020;
[17] Matarazzo T.J.,Kondor D.,Milardo S.,Eshkevari S.S.,Santi P.,Pakzad S.N.,Buehler M.J.,Ratti C. Crowdsourcing bridge dynamic monitoring with smartphone vehicle trips. Commun. Eng. 2022; 1; 29. https://doi.org/10.1038/s44172-022-00025-4.
[18] Matarazzo T.J.,Santi P.,Pakzad S.N.,Carter K.,Ratti C.,Moaveni B.,Osgood C.,Jacob N. Crowdsensing Framework for Monitoring Bridge Vibrations Using Moving Smartphones. Proc. IEEE 2018; 106; 577–593. https://doi.org/10.1109/JPROC.2018.2808759.
[19] Cronin L.,Sadeghi Eshkevari S.,Matarazzo T.J.,Milardo S.,Dabbaghchian I.,Santi P.,Pakzad S.N.,Ratti C. Bridging the Gap: commodifying infrastructure spatial dynamics with crowdsourced smartphone data. Commun. Eng. 2024; 3; 93. https://doi.org/10.1038/s44172-024-00243-y.
[20] Matarazzo T.J.,Cronin L.,Marasco G.,Dabbaghchian I.,Pakzad S.N.,Eshkevari S.S.,Sen D.,Santi P.,Ratti C. Empirical study on smartphone-vehicle trip metadata and bridge modal property estimates, in: Bridg. Maintenance, Safety, Manag. Digit. Sustain., CRC Press, London, 2024; .: pp. 1754–1760 https://doi.org/10.1201/9781003483755-205.