**A Fully Customized Vehicle Scanning System: Field Trials on Two Large-Scale Bridges**

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**Abstract.** Ensuring the structural integrity of bridges is vital for infrastructure safety and long-term sustainability. Indirect Bridge Health Monitoring (BHM), particularly through drive-by bridge inspection, has emerged as a promising and cost-effective alternative to conventional monitoring approaches. By leveraging sensors mounted on moving vehicles, indirect BHM enables the condition assessment of bridges without the need for direct instrumentation, offering scalability and reduced operational disruption. Despite its potential, the practical implementation of indirect BHM in real-world environments remains challenging, especially in reliably detecting structural damage under varying operational and environmental conditions. This paper presents the first study on the development and field validation of a fully customized sensing vehicle designed specifically for indirect BHM applications. The vehicle, equipped with high-resolution accelerometers and integrated automation features, autonomously traverses bridge structures while recording dynamic response data. Two large-scale bridges located in New South Wales (NSW), Australia, were selected as test beds for this investigation. The captured acceleration signals were subsequently analyzed using two robust signal processing and classification frameworks to assess the system’s performance in detecting anomalies while minimizing false positives and false negatives. The field results demonstrate the practical feasibility and reliability of the proposed drive-by inspection approach. This study provides critical insights into the application of indirect BHM under real-world conditions and highlights its potential to serve as a scalable, non-intrusive monitoring solution. The findings contribute to the advancement of next-generation structural health monitoring systems, supporting enhanced infrastructure safety, informed maintenance planning, and the extended service life of critical bridge assets.

**Keywords:** Drive-by bridge inspection, Natural frequency, Bridge monitoring, Time series analysis.

1. Introduction

The prevailing method for monitoring bridge structures in Australia and globally primarily relies on visual inspections and basic testing to assess structural deterioration. These evaluations typically focus on areas of concern, such as support settlement, connection failures, and material degradation. However, this approach is costly, time-intensive, subjective, and qualitative, limiting its effectiveness in ensuring long-term structural integrity [1]. Given the aging infrastructure, a more comprehensive understanding of bridge conditions is essential. Therefore, implementing cost-effective, scientifically grounded, and continuous Bridge Health Monitoring (BHM) systems that accurately reflect a bridge's operational state is crucial.

Traditional direct-SHM involves installing multiple sensors and measurement devices directly on the bridge (see Fig. 1 (a)) [2]. While effective, this method is expensive, labor-intensive, and complex, often making it impractical, especially for bridges in remote locations where a consistent power supply, data storage, and transmission face challenges. Furthermore, direct-BHM systems require ongoing maintenance and sensor replacement, as their lifespan is significantly shorter than that of the bridges they monitor. They are also vulnerable to vandalism and typically designed for individual bridges, limiting their general applicability. Consequently, direct-BHM has not been widely adopted, particularly for the monitoring of short-span bridges, which outnumber long-span structures.

To address these limitations, an alternative indirect BHM approach, also known as drive-by bridge inspection, has gained attention (see Fig. 1 (b)). Unlike direct-BHM, indirect-BHM does not require any sensors or measurement devices to be permanently installed on the bridge itself. Instead, a specialized vehicle equipped with a small number of sensors are used to collect data, see Fig. 2 [3].

This approach leverages the vehicle-bridge interaction (VBI) phenomenon: as the vehicle crosses the bridge, it induces vibrations in the structure, effectively acting as a moving exciter. Simultaneously, the vehicle experiences vibrations from the bridge, functioning as a mobile sensor. By recording the vehicle's dynamic response, valuable insights into the bridge's condition can be obtained. Any structural changes in the bridge manifest as distinct alterations in the vehicle's response patterns, making it possible to detect damage without direct instrumentation of the bridge [4].

A close-up of a bridge

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**Fig. 1.** Illustration of (a) direct BHM; and (b) indirect BHM [5]

A diagram of a truck on a bridge

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**Fig. 2.** Indirect bridge health monitoring concept [6]

As illustrated in Fig. 2, indirect-BHM presents a cost-effective and scalable alternative to direct-BHM, offering a higher spatial resolution since the vehicle traverses multiple points along the bridge span, rather than relying solely on fixed measurement locations. This method has significant potential as a sustainable and economical complement to traditional BHM, enabling more widespread bridge condition assessments.

This paper tackles the challenge of indirect bridge health monitoring by formulating it as an unsupervised semantic segmentation problem. The primary objective is to detect the onset of structural changes by analysing time series data derived exclusively from the acceleration responses of a vehicle as it traverses a bridge, eliminating the need for direct instrumentation of the structure. To facilitate automated and data-driven feature extraction, the proposed method leverages the matrix profile technique [7], which conducts an all-pairs similarity search within the time series to identify patterns and anomalies. Contextual shifts indicative of structural changes are subsequently extracted using the Corrected Arc Crossings (CAC) profile [8, 9], a computational tool that effectively pinpoints transitions within the time series. In addition to the methodological framework, this study introduces, for the first time—a fully customised electric inspection vehicle specifically designed for drive-by bridge monitoring. To the authors' knowledge, such a tailored system has not been previously reported in the literature. The system integrates high-sensitivity accelerometers and autonomous driving capabilities to ensure consistency and repeatability in data collection. Finally, the proposed framework is validated through extensive field testing on two large-scale, operational bridges located in New South Wales, Australia. These experiments demonstrate the feasibility and effectiveness of the iBHM approach under realistic operating conditions.

1. Time Series Change Point Detection

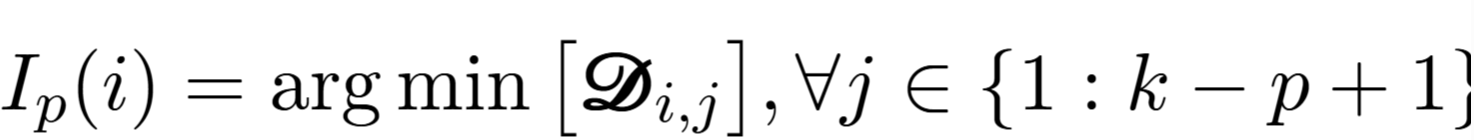
Time series data—sequential measurements collected over time—are widely used to characterize the behavior of systems and structures. Their growing prevalence has driven significant research in time series data mining to uncover meaningful patterns [10]. A core task in this field is change point detection (CPD), which aims to identify moments when the underlying data distribution shifts, often revealing important or unexpected phenomena. Changes in a time series, whether abrupt or gradual, can signify transitions in diverse contexts such as physiological states, climate dynamics, or human activity. In structural health monitoring (SHM), accurately identifying these transitions is critical, as they may signal the onset of structural change. Closely related to CPD is time series segmentation, which divides data into segments of similar behaviour, typically by locating change points [11]. Detecting change points in real-world data remains challenging due to noise, non-stationary trends, environmental variability, and missing data. This study proposes a novel method combining Matrix Profile and semantic segmentation to detect state changes in bridges from moving vehicle time series data. The approach is unsupervised, parameter-free, and requires no prior assumptions or labelled data, making it suitable for both offline and online applications. The algorithmic framework is detailed below.

* 1. Matrix Profile: All Pairs Similarity Joins for Time Series258

Let denotes a sequence of vehicle crossing responses over a bridge, where each represents a real-valued time series corresponding to a single crossing. Although individual crossings may vary in length in time, all are preprocessed to a uniform length . The full concatenated series span the entire observation period where Assuming a structural change occurs, the objective is to detect the change point location, and segment accordingly. If no change occurs, the method should return no segmentation. This is achieved by analyzing the similarity of local subsequences within . A sliding window with length is defined as to slide over where its first location will be on and its last location will be on . Given a collection of subsequences in a time series, the aim of all-pair-similarity-search is to retrieve the nearest neighbor for each subsequence where trivial matches are excluded. A matrix profile, is a vector of the distances between each subsequence with length in and its 1-nearest neighbor where the location of the 1-nearest neighbor can be realised in a companion matrix profile index, .

A black and white background with black text

AI-generated content may be incorrect. (1)

 (2)

A black letter with a white background

AI-generated content may be incorrect.is the distance between and . Note that an exclusion zone is necessary to avoid trivial matches. For instance, matching a subsequence with itself or with another very close in position is considered trivial [9]. These trivial matches are excluded when calculating the minimum distance and identifying the nearest-neighbor index. The matrix profile and its index annotate a time series by capturing the distance and location of each subsequence's nearest neighbor. Together, they enable key time series mining tasks such as motif discovery and anomaly detection [9].

Recall that the *i*-th entry in the matrix profile index is a positive integer *j*, indicating the location of the nearest subsequence to *i*. This pair (*i*, *j*) can be visualized as an arc from *i* to *j*. Each index has exactly one outgoing arc, while it may receive zero, one, or multiple incoming arcs. With the Arc Curve (AC) defined, it can now be used to detect change points in the time series. If a contextual change occurs at time ​, few arcs are expected to cross this point, as most subsequences find matches within the same regime. Thus, the AC reaches its minimum at ​, indicating a potential change in the system—lower AC values suggest stronger evidence of a state transition. While the AC typically reaches its minimum at the change point, it also shows low values near the start and end of the time series due to fewer candidate arcs in those regions. To correct this edge effect, the Corrected Arc Crossings (CAC) is computed by normalizing the AC against an Idealized Arc Curve (IAC) as follows:

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Ultimately, the CAC is a vector of length , matching that of the matrix profile, and is bounded between 0 and 1. The lowest value in the CAC indicates the most likely location of the change point. CAC will be adopted in this study to indirectly monitor the structural integrity of a bridge.

1. A Fully Customized Vehicle Scanning System

This section describes the custom-designed inspection vehicle developed for drive-by bridge assessments. The system is a 1:5 scale electric remote control car fitted with four PCB-ICP393B05 accelerometers (±0.5 g, 0.7–450 Hz) mounted on each wheel’s suspension, and four Honeywell Model 31 Series load cells. Data are collected using an NI cDAQ-9185 CompactDAQ and transmitted wirelessly via a PIX-LINK WR09Q router, then processed and stored using NI-FlexLogger. The vehicle is semi-autonomous, maintaining user-defined speeds and following a magnetic strip using a RoboteQ MGSW1600 sensor for lane tracking. The full system enables efficient, high-fidelity drive-by data acquisition. Fig. 3 shows the setup and data flow. The vehicle has a total mass of 20 kg and an axle distance of 80 cm.

1. Case Studies
   1. Bulli Colliery Bridge

The first case study applies a drive-by inspection method to a pedestrian bridge in Bulli, NSW, Australia—the Bulli Colliery Bridge. This steel girder structure, originally built for coal truck traffic to the Illawarra railway line, now serves as a pedestrian bridge. It has three spans, with the central 23.9 m span selected for analysis. Fig. 4 shows the bridge and its layout. The study begins with direct sensing to determine the bridge’s first natural frequency, which serves as a reference point. Wireless triaxial accelerometers (BeanAir Willow AX-3D) are installed at the bridge’s quarter-span points, sampling at 500 Hz. The vibration response is collected over one minute while pedestrians walk on the bridge, providing random excitation. Fig. 5 shows the acceleration response collected from the sensors at the bridge’s quarters. To estimate the first natural frequency, the frequency domain decomposition (FDD) method is applied to the acceleration signals. This method computes the singular value decomposition (SVD) of the power spectral density (PSD) matrix. The first singular value’s peak, found at 6.7 Hz, represents the estimated first natural frequency (Fig. 6). The second test involves drive-by inspection. Multiple passes of the inspection vehicle are conducted at a constant speed of 0.17 m/s, with acceleration responses recorded from the vehicle’s axle-mounted accelerometers at a sampling rate of 1600 Hz. The bridge remains in operation during this test, with pedestrian-induced random excitations. Fig. 7 shows the acceleration responses from the four axles, and Fig. 8 illustrates the first singular value of the PSD matrix using the FDD method. Comparing Fig. 5 and Fig. 7, it is clear that the acceleration level measured by the indirect drive-by approach is much higher than the direct sensing approach. From Fig. 8, the first frequency of the bridge is estimated to be 6.42 Hz.

A computer parts and components of a car

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**Fig. 3.** Illustration of the fully customized inspection vehicle and its key measurement components.

A small vehicle on a bridge

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1. (b)

**Fig. 4.** Illustration of: (a) inspection car traversing the bridge deck, and (b) side and underside views of the bridge [source: Google Map].

A screenshot of a graph

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**Fig. 5.** Acceleration time series from direct sensing (a) sensor located at quarter-span, (b) sensor located at mid-span and (c) sensor located at three-quarters of the span.

A screen shot of a graph

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**Fig. 6.** Illustration of the first singular value from direct inspection tests.

* 1. UNSW Bridge

The second case study involves a pedestrian bridge located on the University of New South Wales (UNSW) campus in Sydney, (see Fig. 9). This simply supported steel structure spans 17 meters in length and is 80 cm wide. As in the previous case, a direct sensing campaign is first conducted to identify the bridge’s natural frequencies, serving as ground truth. This is followed by an indirect sensing assessment using the drive-by inspection approach. The identified frequency of the bridge from the direct measurement and indirect measurement is, respectively, presented in Fig. 10 and Fig. 11 which appear to be at 6.65 Hz. For the sake of brevity, the time responses are not presented.

A graph of a waveform

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**Fig. 7.** Illustration of acceleration time series from indirect sensing, (a) front-right axle, (b) front-left axle, (c) rear-right axle, (d) rear-left axle.

A graph of a frequency

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**Fig. 8.** Illustration of the first singular values from five independent indirect inspection tests. The left and right red dashed lines respectively represent the averaged first natural frequency of the structure and the driving frequency of the electric motor.

A person walking on a walkway

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**Fig. 9.** Illustration of the UNSW pedestrian Bridge.

A graph of a frequency

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**Fig. 10.** First singular values from five separate direct inspection tests. The red dashed line marks the average first natural frequency of the structure.

A graph of a frequency

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**Fig. 11.** Illustration of the first singular values from five independent indirect inspection tests. The red dashed lines indicate the average first natural frequency of the bridge (left) and the driving frequency of the electric motor (right).

Following the successful identification of bridge fundamental frequency using the drive-by framework—and the consistency observed with results from direct measurements—multiple vehicle runs were conducted on both bridges under operational conditions, using the same measurement settings (e.g., speed and sampling frequency) as previously specified. Additionally, for the UNSW bridge, a controlled change was introduced by adding mass at mid-span to alter its dynamic characteristics.

1. Change Point Detection Results

The acceleration responses from the four vehicle-mounted accelerometers are pre-processed as follows. First, the Power Spectral Density (PSD) matrix is computed using the Frequency Domain Decomposition (FDD) method, and its first singular value is extracted. A bandpass filter between 1 Hz and 10 Hz is then applied, producing 900 spectral lines. These spectra are normalized between 0 and 1 using min-max normalization. Next, a data sequence is formed by concatenating the 900 spectral lines from multiple vehicle passes over both the intact and altered bridge states. Finally, the Matrix Profile and corresponding Corrected Arc Curve (CAC) are computed for each sequence. The CAC minimum is expected to indicate the point of change in bridge condition. In cases with no induced change—such as the Bulli Colliery Bridge—no significant CAC extremum should appear.

Overall, 50 samples of vehicle runs are collected from each bridge. For the sake of data augmentation, 5 samples out of these 50 samples are randomly selected the obtained spectrum is averaged to generate one sequence.

Fig. 12 shows 30 concatenated sequences from the UNSW bridge, all recorded in its intact state. As expected, the corresponding CAC profile remains close to 1 throughout, indicating no change in the bridge’s condition. In contrast, Fig. 13 presents a case where the first 20 sequences are from the intact bridge, followed by 10 sequences from the altered state. The CAC profile clearly identifies the change point in the series. To further validate the method, this test was repeated 1000 times. The results for the intact-only sequences and the mixed-condition sequences are shown in Fig. 14 (a) and Fig. 14 (b), respectively. As observed across 1000 independent analyses, the proposed framework consistently demonstrates strong performance. Fig. 15 presents a similar 3D contour plot for the Bulli Colliery Bridge. As no structural change was introduced, the CAC profile remains consistently near 1. These results confirm the effectiveness of the proposed framework and its robustness against both type I and type II errors in structural health monitoring. They also provide a basis for defining reliable threshold values for change detection.

1. Conclusions

This study introduced a Matrix Profile-based approach for indirect direct bridge health monitoring, removing the need for large datasets or supervised learning. Following the introduction of the matrix profile, the Corrected Arc Crossing (CAC) method was developed to pinpoint changes in the context of the data-generating system. Unlike other drive-by inspection techniques, this approach operates in an unsupervised learning setting—requiring no labelled data, minimal input data, and no hyperparameter tuning. Method’s effectiveness was validated through field investigations on two large-scale predestrain bridges in the state of NSW, Australia. In all cases examined, the method accurately detected the point at which the bridge's condition changed. Moreover, it did not produce any false alarms when the bridge remained in an unchanged state. These results highlight the method’s potential for continuous monitoring of large-scale structures in resource-constrained settings. Future work should explore the effects of long-term environmental trends and extend validation across diverse bridge types and damage scenarios to enhance generalizability.

A graph of a sample

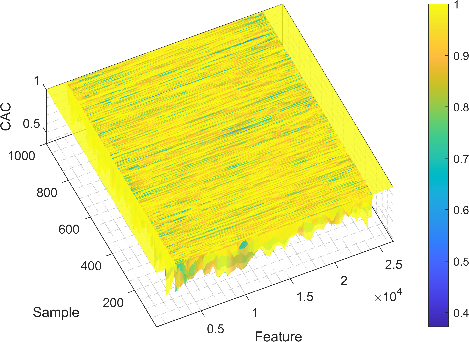
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**Fig. 12.** Top: Sequence consisting of 20 vehicle runs followed by 10 additional runs over the intact UNSW bridge. Bottom: Corresponding Corrected Arc Curve (CAC) profile showing no significant change, confirming structural consistency.

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**Fig. 13.** Top: Sequence comprising 20 vehicle runs over the intact UNSW bridge, followed by 10 runs over the altered bridge. Bottom: Corresponding Corrected Arc Curve (CAC) profile indicating the location of the structural change.

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1. (b)

**Fig. 14.** Corrected Arc Curve (CAC) profiles obtained from 1000 independent series: (a) all 30 sequences correspond to the intact state of the bridge; (b) 20 intact sequences followed by 10 sequences from the altered bridge state.

A yellow square with lines and numbers

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**Fig. 15.** Corrected Arc Curve (CAC) profiles from 1000 independent series collected from the Bulli Colliery Bridge, where no structural change was present.

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