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Unsupervised online anomaly detection in road bridges from single-point acceleration data

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ABSTRACT

Ensuring the safety of civil infrastructure, particularly bridges, is essential. Yet, conventional multi-sensor monitoring systems are often cost-prohibitive for large bridge networks. To address this, we propose an unsupervised online anomaly detection framework that relies on single-accelerometer data. Dynamic characteristics are extracted through random decrement and autoregressive modeling, while Mahalanobis Distance quantifies structural changes with reduced outlier influence. Temperature effects are corrected using a machine learning model. The framework was validated on four bridge types over more than one year of monitoring. Results show that the method effectively distinguishes transient events, such as sensor malfunctions or abnormal amplitudes, from permanent structural changes, exemplified by pavement replacement. In the latter case, the Mahalanobis Distance mean increased from 5.2 to 11.5 (121 %), demonstrating sensitive detection of system changes. These findings highlight the framework's potential as a cost-effective tool for early anomaly warning and preventive maintenance in large bridge inventories.

1. Introduction

Bridges are vital components of civil infrastructure, supporting both economic activities and daily life. Ensuring their ongoing safety and functionality is therefore critical. Structural health monitoring (SHM) has emerged as a key approach to this end. SHM involves assessing structural change in real time or at regular intervals, facilitating early damage detection and providing data to guide maintenance decisions. This contributes to enhanced structural safety and reduced life cycle costs. Over the past several decades, SHM has advanced considerably, driven by improvements in sensor technologies, data processing algorithms, and damage detection methods.

Traditional bridge SHM methods are effective in analyzing the dynamic characteristics of structures through multi-sensor-based modal analysis techniques. However, their real-world implementation faces several challenges. These methods often require the installation of numerous sensors across an entire structure, leading to high upfront costs. In addition, ongoing expenses for cabling, power supplies, and maintenance in case of sensor failure can be significant. Furthermore, successful SHM implementation demands engineers with expertise not only in structural behavior under various conditions (e.g., operational, damaged, or safety limit states) but also in understanding the broader context, including social, political, financial, and organizational factors. As a result, SHM technologies are currently applied mostly to high-value bridges that are critical to local communities (Aktan et al., 2024). At the national level, the majority of bridges are still monitored through conventional visual inspections by personnel.

In many instances, a single bridge manager oversees a large number of bridges, often relying on minimal-cost outsourcing services to gather basic information. Maintenance priorities were determined based on these limited data. Routine maintenance generally involves visual inspections, which focus primarily on documenting visible signs of deterioration in bridge components. Despite these efforts, bridge collapses continue to occur in Korea. One such incident, shown in Fig. 1, involved significant structural cracking that went undetected until the collapse occurred.

In response, the Korean government has recently launched efforts to digitize bridge monitoring by installing a minimal number of sensors, aiming to enable preemptive action before structural failure occurs. Since 2022, a nationwide sensor deployment program has been

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underway, with monitoring systems installed on 1068 bridges by 2024. As previously mentioned, owing to the large number of sites, each bridge was equipped with only one sensing system, typically with no more than two accelerometers. However, the challenge lies in the fact that most existing SHM technologies are designed to analyze detailed dynamic behaviors using a dense array of sensors. Consequently, these methods are not well-suited for low-instrumentation environments, highlighting the need for new methodologies capable of effectively utilizing the limited data from just one or two sensors.

SHM research has evolved based on dynamic response data from multiple sensors and environmental variables, such as temperature. In recent years, there has been a growing focus on anomaly detection using various damage scenarios and actual response measurements from real bridges. This trend reflects the increasing demand for real-time detection of abnormal behavior in infrastructure systems. SHM approaches are generally categorized into contact and non-contact methods, both of which collect response and damage data from bridges. These data are processed using statistical techniques or machine-learning algorithms to support prediction, classification, and clustering for anomaly detection.

Non-contact vision-based SHM methods use image data from unmanned aerial vehicles, closed-circuit television cameras, and other sources. Techniques based on deep learning for object detection and segmentation, such as Faster R-CNN, YOLO, and U-Net, have proven effective in identifying visual damage such as cracks, spalling, and corrosion (Tran et al., 2023; Gan et al., 2024). In vision-based displacement measurement studies, a novel 2D VDM method was proposed that utilizes only two cameras combined with coded artificial targets and a homography-based self-calibration logic, thereby enabling 3D displacement monitoring (Zhang et al., 2024). However, these methods are limited by their inability to handle variations in lighting conditions and their inability to detect internal or subsurface damage. Additionally, they may not fully capture the dynamic behavior of structural anomalies.

Thermal imaging-based SHM has enhanced defect detection accuracy by combining infrared thermal images with techniques such as image mosaicking, K-means clustering, and custom optimization algorithms (Ichi and Dorafshan, 2022; Omar et al., 2018). Beyond identifying the location and area of defects, a novel empirical formula has been proposed by integrating FEA to quantitatively estimate the depth of internal defects in concrete slabs (Naik et al., 2024). Pulsed thermography experiments were conducted on RCC slabs with embedded artificial defects, and thermal diffusivity was calculated through FEA simulations. Based on this, an empirical formula linking defect depth with the product of observation time and thermal diffusivity was derived, achieving approximately 40 % lower error compared to conventional linear models. However, this approach is limited to detecting defects at depths of about 5 cm or less and has so far only been validated under laboratory conditions rather than in outdoor environments.

In addition, a method combining UAV-based infrared thermography with YOLOv5 and Mask R-CNN was proposed for the automatic detection of delamination in concrete bridge decks (Aljagoub et al., 2025). By integrating real UAV-captured images with numerically simulated synthetic data, a large-scale dataset was constructed, addressing the issue of data scarcity and improving the generalization performance of the models. This approach overcomes the subjectivity of traditional threshold-based methods and enhances the detection of deep delamination. However, limitations remain regarding system implementation conditions and real-time data processing.

In this context, thermal imaging–based studies are highly sensitive to environmental factors such as ambient temperature, wind, and material properties, and their practical applicability is constrained by the need for high-resolution equipment and costly infrared sensors.

Graph theory–based SHM has modeled sensor networks using Graph Neural Networks (GNNs) and Graph Convolutional Networks (GCNs) for applications such as damage detection and mode shape estimation (Bloemheuvel et al., 2021; Li et al., 2021a). This approach offers the advantage of enabling relatively robust anomaly detection even in large-scale infrastructure systems with complex sensor networks. More recently, a Dual-Graph Neural Network (DGCN) framework was proposed to further enhance structural damage detection and localization (Wijethunga et al., 2025). This method simultaneously models a topology graph based on sensor layouts and a feature similarity graph, thereby overcoming the limitations of single-graph approaches. In addition, 1D-CNN preprocessing was introduced to improve noise robustness and computational efficiency, achieving over 99 % accuracy on benchmark datasets. Notably, the framework maintained high performance under noisy conditions and limited data scenarios, demonstrating strong potential for practical implementation. However, research that applies this approach to large-scale infrastructure with multi-sensor systems and validates it using real-world field data remains limited.

Recent research in SHM has increasingly focused on deep learning-based time-series models for more effective anomaly detection in bridges. Yang et al. (2020) introduced a spatiotemporal hybrid model combining convolutional neural networks (CNNs) and gated recurrent units (GRUs), demonstrating its damage detection performance using a



Fig. 1. Bridge collapse case in South Korea.

scaled bridge model. Li et al. (2021b) represented the dynamic responses of multiple cables in a cable-stayed bridge as a graph structure, employing a spatiotemporal graph convolutional network to detect pattern changes and identify faulty sensors. To address the challenge of pseudo-normal data, Deng et al. (2023) transformed the frequency-domain information obtained through a Fast Fourier Transform into Gramian Angular Field images and used a CNN to quantify the data quality. Teng et al. (2024) applied a convolutional autoencoder (CAE) for unsupervised damage detection on a steel truss bridge and demonstrated superior performance in terms of reconstruction accuracy and clustering quality compared to long short-term memory (LSTM) and GRU-based autoencoders. Kim et al. (2025) integrated dynamic responses and environmental data into a bidirectional time-series LSTM model, using Bayesian optimization to create a high-performance predictive framework. Their model successfully detected anomalous vibration events under strong-wind conditions, highlighting its potential for real-time risk monitoring. More recently, Dibiantara et al. (2025) advanced architectures incorporating MPCA, biGRU, and attention mechanisms within encoder-decoder frameworks have been proposed, enabling the learning of complex, nonlinear spatiotemporal patterns for high-performance SHM systems.

Deep learning-based approaches, however, face several challenges in practical implementation, including the difficulty of acquiring large-scale labeled datasets, limited model interpretability due to the black-box nature of deep networks, and the risk of overfitting. Considering these limitations, statistics-based SHM methods remain a valuable research direction because they typically involve lower-dimensional data, offer greater interpretability, and allow mathematically rigorous explanations. For example, Gul and Necati Catbas (Gul and Necati-Catbas, 2009) applied the random decrement (RD) technique and autoregressive (AR) modeling to extract features from dynamic response data collected from a laboratory-scale steel beam structure. They successfully detected boundary condition changes using Mahalanobis Distance (MD)-based anomaly detection. Similarly, Yao and Pakzad (2012) proposed a statistical pattern recognition approach that utilizes Ljung–Box statistics computed from AR model residuals and a spectral domain metric known as the Cosh Spectral Distance. The experimental results showed that both the MD-based method and the Cosh Spectral Distance approach delivered more stable and reliable damage detection performance.

Meixedo et al. (2021) proposed an anomaly detection method for railway bridges that AR modeling, principal component analysis, and MD. By incorporating finite element method (FEM)-based damage simulations alongside real sensor data, the approach achieved high precision, maintaining a false detection rate below 1 %. In a subsequent study (Meixedo et al., 2022), an autoregressive model accounting for exogenous variables was integrated with K-means clustering. Anomalies were detected by comparing dissimilarity metrics between clusters, successfully identifying simulated damage scenarios involving a 5 % reduction in structural stiffness. Additionally, Svendsen et al. (2022) compared the performances of supervised and unsupervised anomaly detection methods using response data from a railway bridge. Their findings revealed that the unsupervised approach achieved comparable accuracy, demonstrating its practical applicability. To date, SHM research on anomaly detection has primarily focused on structures with simpler damage mechanisms or those more conducive to sensor deployment, such as railway bridges, long-span bridges, and steel truss systems. These methods typically rely on data from multiple sensors. However, for road bridges, which are influenced by more complex environmental factors such as traffic loading, temperature fluctuations, and wind, there is a notable gap in studies employing statistical anomaly detection techniques based on actual dynamic responses.

In the field of SHM, it is crucial to pursue not only advanced deep learning techniques but also interpretable, robust statistics-based approaches capable of effectively managing environmental variability. Currently, there is a pressing need for more field-oriented studies that apply these methods to various structural types under actual loading conditions. SHM methodologies should be selected according to the specific target structures and monitoring objectives (Choi et al., 2021). This study focuses on detecting structural changes in global dynamic behavior using only a single sensor, which enables the application of low-dimensional, stable statistical features and machine learning techniques to small datasets. Therefore, the acceleration responses were preprocessed with the RD technique to extract free-vibration signatures, and daily features were derived using an AR model. One year of monitoring data was analyzed to capture long-term variations, with temperature compensation performed using an extreme gradient boosting (XGBoost) regression model. MD was then used as a distance-based metric to quantify deviations and detect potential damage. The proposed approach, which combines statistical and machine learning techniques, is well-suited for deployment across multiple bridge systems using a single sensor, rather than a dense sensor network. This enables robust damage detection with limited data and offers a practical solution for large-scale infrastructure monitoring.

2. Bridge description and monitoring system

This study considers four types of bridges: reinforced concrete slab (RCS), reinforced concrete frame (RCF), prestressed concrete I-girder (PSC-I), and steel box girder (STB) structures. These bridges are located on national highways rather than in city centers or expressways and are classified as Grade 3 under Korea's bridge maintenance regulations (Korea Authority of Land and Infrastructure Safety (KALIS and), 2021), indicating a relatively low level of structural importance. As a result, minimal maintenance efforts have been allocated. Routine assessments consist of visual inspections conducted approximately twice a year, with no detailed structural evaluations performed to date. Although historical records show no major visible damage from the perspective of bridge managers, the current inspection-based maintenance system cannot ensure the prevention of future catastrophic failures. Furthermore, the government agency responsible for these bridges manages dozens of similar structures under comparable conditions, underscoring the need for an improved maintenance strategy. However, limited human and financial resources pose significant barriers to the implementation of comprehensive preventive maintenance. Consequently, a practical compromise is required that introduces only a minimal increase in cost while enabling timely detection of critical structural changes in a rational and scalable manner.

Accordingly, a minimal sensing system consisting of one accelerometer and a single temperature sensor was implemented on each bridge. Fig. 2 illustrates an example of a sensing system installed on a PSC-I bridge, where the sensors are mounted on the underside of the flange of the interior girder at the midspan. For bridges without girders such as RCS, RCF, sensors were attached to the underside of the deck at midspan. For the dynamic response monitoring of the structure, we utilized the internal micro-electro mechanical systems accelerometer of the S-CUBE node, developed by the South Korean company SMARTC&S. The key specifications for this sensor include a measurable signal bandwidth of 0–50Hz. To ensure accurate data acquisition without aliasing, a sampling frequency of 100Hz was employed. This rate is consistent with the sensor's selectable range of 50–200 SPS (samples per second) and satisfies the Nyquist-Shannon sampling theorem for the given signal bandwidth, ensuring a faithful representation of the structural vibrations. The accelerometer's measurement range was configured to $\pm$2.0g, which corresponds to a sensitivity of 420 mV/g. For the collection of temperature signals, we used a separate wireless sensor node (BEACON model, also from SMARTC&S) which transmits data via Bluetooth low energy. It is crucial to distinguish between the temperature sensor's intrinsic sampling rate and the main data logger's recording frequency. The BEACON sensor itself sampled the ambient temperature at 5Hz. Our central data acquisition system, operating at a unified frequency of 100Hz for all incoming signals, recorded the most



Fig. 2. Example of a sensing system for a PSC-I bridge.

recently received temperature value at each 100Hz timestamp. Consequently, a single temperature reading was logged for approximately 20 consecutive timestamps before being updated by a new transmission from the BEACON sensor. This methodology ensures that all collected data, both vibration and temperature, are synchronized to a common time base, facilitating direct correlation and analysis while accurately reflecting the slower-changing nature of thermal conditions. This study explored methods for effectively utilizing the accumulated data for structural monitoring and anomaly detection.

3. Baseline modeling

3.1. Feature extraction for structural change detection

In this study, structural changes in bridges were detected by extracting quantitative features from the measured dynamic response data using an AR model. The AR model is a widely used statistical tool for analyzing stationary time-series data, where the current response is represented as a linear combination of past values (Eq. (1)).

$$x_t = \sum_{i=1}^{k} \varnothing_i x_{t-k} + \varepsilon_t \tag{1}$$

where x_t and ε_t denotes the observed response at time t, and ε_t represents the error term, which is assumed to be white noise. The coefficients $\varnothing_i$ are the AR parameters, and k indicates the order of the model, i.e., the number of independently estimated parameters.

Bridge structures experience continuous random vibrations during operation. In the absence of sudden environmental changes or structural damage, the dynamic responses are generally considered statistically stationary. The augmented Dickey-Fuller (ADF) test (Dickey et al., 1979) applied to the acceleration data yielded a test statistic of −31.75, which was well below the 1 % critical value (−3.43), with a p-value <0.001. These results confirm that the time series is stationary, exhibiting neither trend nor seasonality.

However, any violation of this stationarity, caused by changes in structural stiffness would lead to a noticeable shift in the parameters of the AR model. This suggests that AR parameters can serve as damage-sensitive features (Farrar and Worden, 2012). Due to their compact representation and ease of automated extraction from measured data, AR parameters are well-suited for real-time structural health monitoring and can be effectively used as input features in machine learning-based damage detection algorithms.

However, directly applying the AR model to data from operational bridges presents several challenges. Bridges are continuously exposed to unpredictable excitations such as irregular traffic loads and wind loads, resulting in dynamic responses that fluctuate over time (Ho and Nishio, 2020). When an AR model is applied directly to such highly variable raw data, the estimated model parameters reflect not only the intrinsic dynamic characteristics of the structure but also the statistical properties of the input excitation, thereby reducing the consistency and reliability of the results.

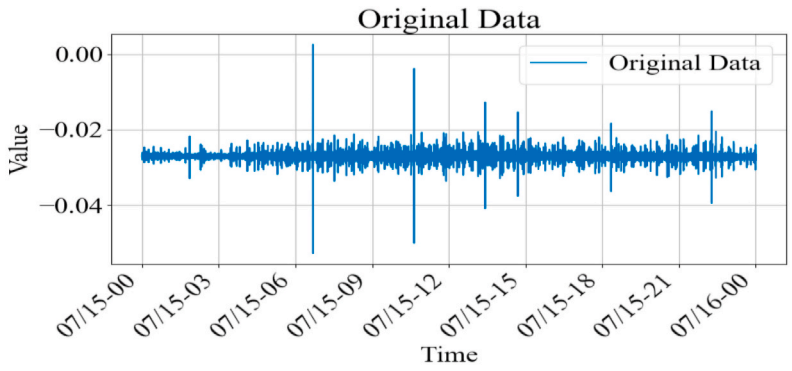
To address this issue and standardize data quality, the present study introduces the RD technique (Brincker and Amador, 2022) as a pre-processing method. Fig. 3(a) presents the raw acceleration data for one day. After setting a trigger line, 15-s segments were extracted following the threshold, which are illustrated in Fig. 3(b). Based on these segmented matrices, RD was applied to characterize the daily free vibration patterns, as shown in Fig. 3(c). The RD technique extracts the free-vibration response, known as the RD signature, from irregular vibration signals. As shown in Eq. (2), the RD signature is obtained by averaging selected data segments identified based on a pre-defined triggering condition.

$$D_x(\tau) = \frac{1}{N}\sum_{i=1}^{N} x(t_i+\tau), where\ x(t_i) = a \tag{2}$$

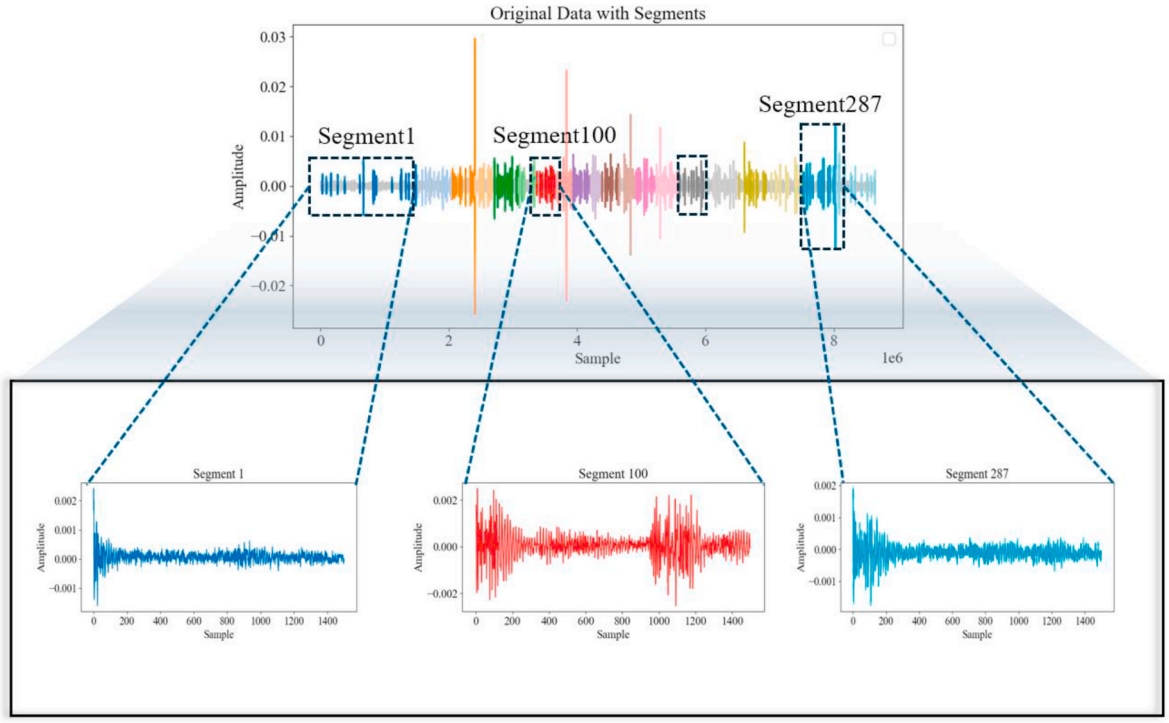
Where, $D_x(\tau)$ represents the RD signature of the time series data x(t), and τ denotes the number of data points (lag) considered following the fulfillment of the triggering condition. N indicates the total number of triggering points. The parameter a defines the triggering level. The condition of Eq. (2) corresponds to the simplest and most commonly used condition, known as the level-triggering condition.

The RD signature extracted through this process effectively filters out the randomness of ambient excitations, producing a signal that closely approximates the free-vibration response and reflects only the structure's intrinsic dynamic characteristics. As a result, applying the AR model to the RD signature yields more stable and consistent features. Additionally, because the RD process operates on segmented portions of the data rather than the entire dataset, it enhances computational efficiency, making it ideal for real-time online monitoring applications. In this study, the triggering condition is defined as five times the standard deviation above the mean of the entire dataset. This empirically determined threshold isolates the meaningful dynamic behavior of road bridges and can be adjusted based on the structural characteristics of each bridge.

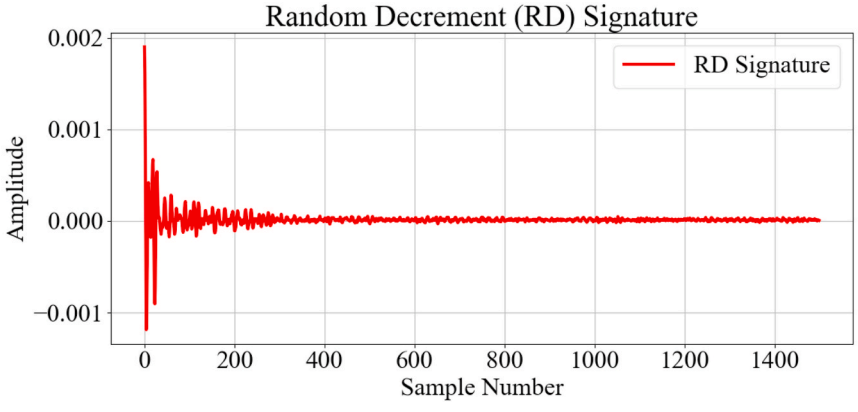
Although the accuracy of the AR model generally improves with a higher model order k, excessively large orders can lead to overfitting,



(a)



(b)



(c)

Fig. 3. Process of transforming raw data into the daily free vibration pattern; (a) Daily raw acceleration data, (b) Segmentation, (c) Daily free vibration pattern.

capturing noise instead of the true structural behavior. Conversely, an excessively low order may fail to capture the essential physical characteristics of the response. Therefore, determining an appropriate model order is crucial. In this study, the Akaike information criterion (AIC) (Akaike, 1974) was employed to evaluate the model performance and identify the optimal order suitable for bridge monitoring applications (Eq. (3)).

$$AIC_k = n\,ln\,\hat{\sigma}_k^{\,2} + 2k \tag{3}$$

where $\hat{\sigma}_k$ denotes the estimated variance of the residuals from the AR model, n is the total number of data points, and k represents the number of AR parameters (i.e., the model order).

The AIC allows for a balanced evaluation of both the model complexity and goodness of fit, and the optimal model order k is defined as the value corresponding to the minimum AIC. Since Eq. (3) was applied to the results of Eq. (2), parameter n is equivalent to N, and is the number of triggering points. As shown in Fig. 4(a), the optimal model order was determined based on AIC analysis. To account for the variability in bridge behavior, the AIC was computed using data collected over a 150-day period. The distribution of optimal orders is presented as a histogram in Fig. 4(b). The three most frequently selected optimal orders were 18, 19, and 20 in descending order. To capture the structural behavior comprehensively, the model order was uniformly set to 20 for all subsequent feature extractions.

For the STB type bridges, one year of monitoring data was divided into daily windows, and the RD signature was extracted from each segment using Eq. (2). The parameters were then obtained by applying the AR model defined in Eq. (1). As shown in Fig. 5, the extracted parameters exhibit variability within a specific range for each model order, although the magnitudes and central tendencies of these distributions have not yet been quantified. Fig. 5 presents the distributions of AR(1) through AR(20) parameters estimated on a daily basis, and these distributions were tracked and compared across a two-year monitoring period.

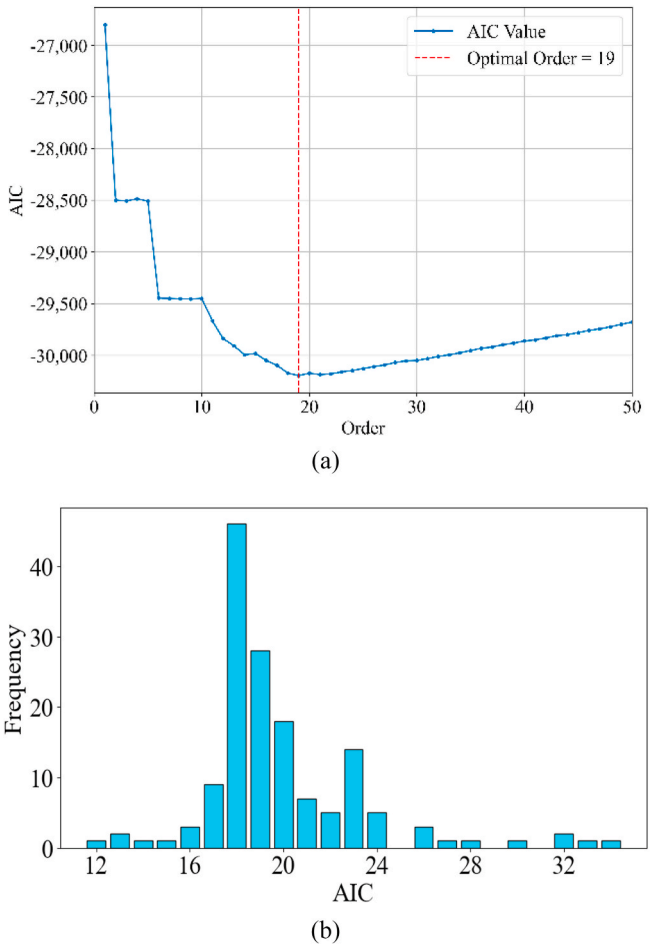


Fig. 4. (a) Determination of the optimal AR model order based on AIC for a single day of measurement data (b) Distribution of optimal AR model orders derived from AIC analysis using 150 days of monitoring data.

3.2. Feature modeling

As shown in Fig. 5, the current data alone does not provide sufficient information to determine the presence of anomalies. Therefore, a meaningful quantitative metric is necessary. To address this, this study uses the MD, a statistical measure that accounts for the distribution of multivariate data and quantifies the deviation of a specific data point from that distribution. When the AR parameter values in Fig. 4 are treated as a feature vector ($v_\varnothing$), representing the dynamic characteristics of the bridge, the MD can be calculated using Eq. (4).

$$d_m(v_\varnothing, \mu_\varnothing) = \sqrt{(v_\varnothing - \mu_\varnothing)^T \Sigma^{-1} (v_\varnothing - \mu_\varnothing)} \tag{4}$$

Where $\mu_\varnothing$ represents the mean vector, and Σ denotes the covariance matrix of the extracted AR parameter set.

The covariance matrix in Eq. (4) was calculated by first acquiring the acceleration data over a certain monitoring period and then extracting the AR parameters across several days. However, for road bridges, the traffic load is random in nature, and the data are likely to include outliers owing to the influence of varying vehicle loads, as illustrated in Fig. 6. These outliers can heavily distort the covariance matrix, as extreme values may dominate the estimation and result in unrealistic MD values. To address this, a robust method of covariance estimation is needed. In this study, a Minimum Covariance Determinant (MCD) estimator was employed. MCD identifies a subset of the dataset that minimizes the determinant of the sample covariance matrix, thereby reducing sensitivity to outliers. A Fast-MCD algorithm is typically used for computational efficiency (Hubert et al., 2018). The implementation in this study utilized the "MinCovDet" module available in the Scikit-learn library (Python) (Pedregosa et al., 2011).

3.3. Temperature compensation

Fig. 6 shows the MD values derived from the acceleration data using the methods outlined in Sections 3.1 and 3.2, along with the corresponding daily average temperature. As seen in Fig. 7, the MD values exhibit significant variability during winter, particularly when temperatures are low. This fluctuation does not necessarily indicate structural damage but rather reflects seasonal non-stationarity in the data, which impacts the AR model parameters. A sharp increase in MD is observed

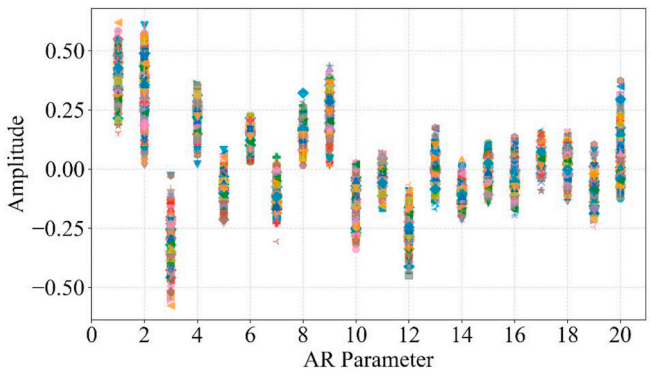


Fig. 5. Parameter distributions of the AR model representing the free vibration.

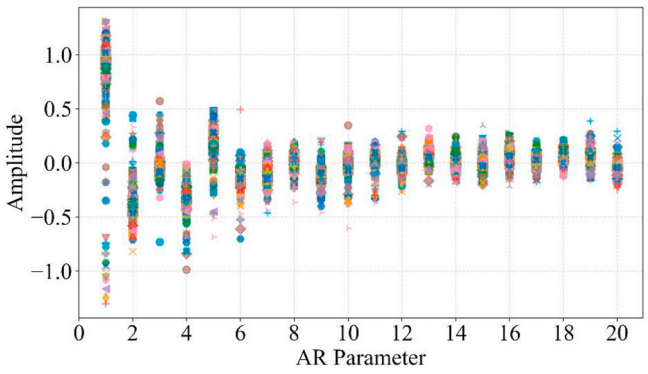


Fig. 6. Example of AR feature distributions extracted from acceleration data with anomalies.

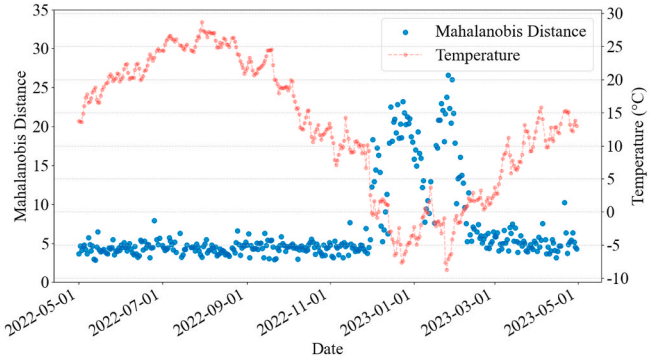


Fig. 7. Relationship between Mahalanobis Distance transformed from dynamic feature matrix and measured temperature.

when temperatures fall below approximately 5 °C. This trend is consistent with prior studies (Yakut and Yura, 2002; Sembiring et al., 2025; Sun et al., 2018), which identified temperature-induced stiffness variations, such as hardening and crystallization effects in bridge bearings and freeze-thaw actions in concrete, as potential contributors. Since such abrupt changes may be misinterpreted as anomalies in online monitoring, temperature compensation is crucial for reliable anomaly detection.

As shown in Fig. 7, the relationship between MD and temperature is clearly nonlinear, making it difficult to fully compensate for temperature effects using traditional statistical methods like linear regression. To overcome this challenge, this study employs a machine-learning-based regression model, extreme gradient boosting (XGBoost), which effectively captures the complex nonlinear relationship between temperature and AR parameters.

The temperature compensation procedure is as follows as shown in Fig. 8: First, the daily average temperature measured at the bridge is preprocessed and used as the input feature for the XGBoost model. Each of the 20 AR parameters was treated as a separate dependent variable, resulting in the construction of 20 individual XGBoost regression models to learn the influence of temperature on each parameter independently. Using these trained models, the predicted AR parameter values are calculated for all time points, based solely on the corresponding temperature data. These predicted values represent the theoretical variations in the AR parameters due to temperature changes alone. Finally, the temperature-compensated AR parameters are obtained by subtracting the predicted values from the measured AR parameters. The MD values computed using these compensated parameters are presented in Fig. 9. The results demonstrate that temperature effects were successfully removed, leading to a more consistent distribution of MD values and indicating that baseline modeling for anomaly detection was

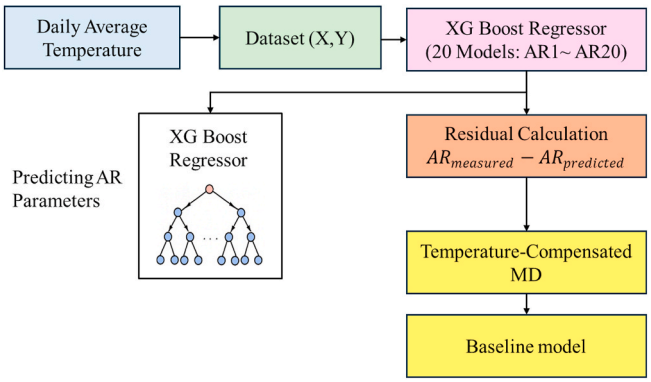


Fig. 8. XGBoost-based process for temperature compensation of Mahalanobis Distance.

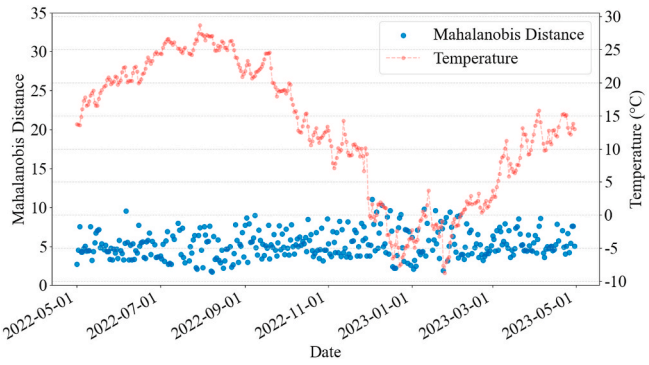


Fig. 9. Temperature-compensated Mahalanobis Distance and measured temperature.

effectively achieved.

4. Online monitoring strategy for structural change detection

This section outlines the proposed online monitoring strategy for data-driven detection of structural changes. As shown in Fig. 10, the strategy consists of two phases: an initial offline phase, where a baseline model is developed to represent the normal behavior of the bridge, followed by an online phase, where real-time detection of structural changes is performed based on this reference. The approach is designed to continuously monitor the structural integrity of the bridge using data from a single accelerometer, providing early warnings in case of significant structural changes. The procedures of this framework were carried out in a Python environment.

4.1. *Offline phase: baseline modeling*

To successfully implement an online monitoring framework, it is essential to first construct an accurate model of the normal conditions of the bridge to serve as a baseline for comparison. Section 3 demonstrates that the natural variability in the dynamic characteristics, particularly those by environmental factors like temperature, can be effectively captured and modeled. Building on these findings, the specific procedures for baseline modeling during the offline phase are outlined as follows:

Data collection and preprocessing: To effectively capture the seasonal variability of the bridge, long-term monitoring data, including at least one year of acceleration and temperature measurements, should be collected. The data were segmented into 24-h windows to facilitate consistent daily assessments of the bridge's condition.

Feature extraction: As detailed in Section 3.1, the RD technique was

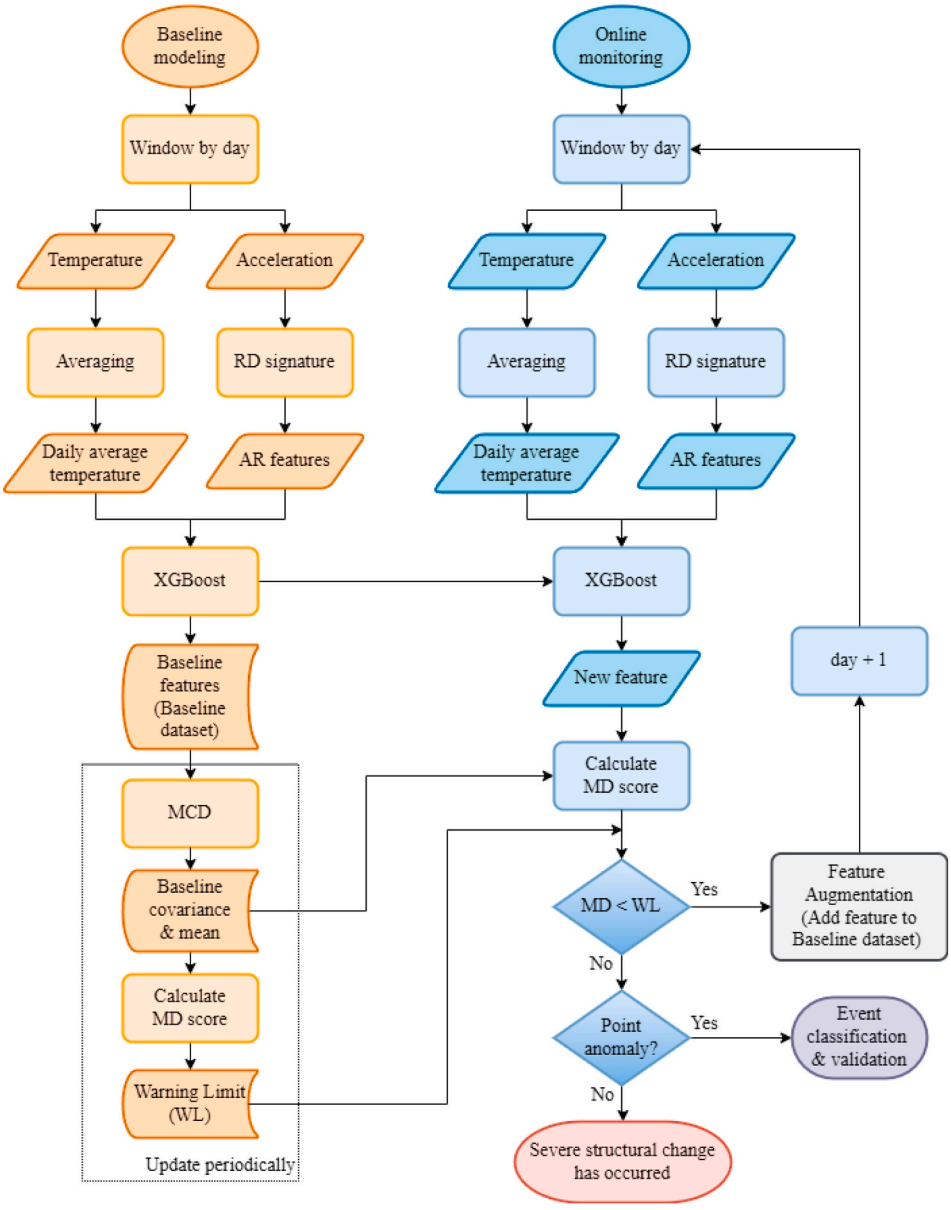


Fig. 10. Flowchart of the proposed online monitoring strategy.

applied to the daily acceleration data to extract the RD signature, which reflects the system's intrinsic dynamic behavior. An AR model with a pre-defined optimal order (k = 20) was then fitted to the RD signature, resulting in a daily feature vector comprising 20 AR coefficients.

Temperature compensation: Daily temperature measurements were averaged to obtain the daily average temperature. The XGBoost regression model described in Section 3.3, the nonlinear relationships between temperature and each of the 20 AR parameters were learned. The trained models were then used to isolate and remove the temperature effect from the original AR feature vectors. Consequently, a baseline feature dataset independent of temperature variation was constructed.

Definition of normal condition and warning limit setting: The baseline feature dataset was used to statistically define the normal behavior of the bridge. To minimize the influence of outliers and capture only the core characteristics of the data distribution, the MCD method introduced in Section 3.2 is applied. MCD robustly estimates the mean vector and covariance matrix from the baseline dataset, which are then considered to represent the center of the Gaussian distribution corresponding to the normal state of the bridge. Using the estimated mean and covariance, MD scores were calculated for each data point in the baseline dataset. Based on the distribution of these MD scores, a statistical warning limit (WL) was established to distinguish between normal and potentially anomalous behavior. In this study, an outlier detection approach based on the interquartile range rule was used, with WL defined by Eq. (5).

$$WL = Q3 + k(Q3 - Q1) \tag{5}$$

where $Q1$ and $Q3$ denote the first and third quartiles of MD scores, respectively, and k is a sensitivity-adjusting coefficient. Since the distribution of MD scores may vary across bridges, the value of k should be determined by the bridge manager. Typically, a value of 1.5 is used, but a higher value may be chosen to detect only extreme anomalies.

Periodic update: The baseline model is not fixed; it can be updated periodically to reflect gradual structural aging or environmental changes. When new data labeled as normal during the online monitoring phase were added to the baseline dataset, MCD estimation and MD computation were performed again. This process updates the mean vectors, covariance matrices, and WL, thereby continuously enhancing

the model's robustness and accuracy.

4.2. Online phase: online monitoring and structural change detection

Once the baseline model was successfully established during the offline phase, the system transitioned to the online monitoring phase for real-time data processing. In this phase, the procedure is automatically executed upon receiving new data, allowing for daily assessments of the bridge's current condition and the detection of potential anomalies.

Acquisition of new data and feature extraction: In accordance with the monitoring cycle (day + 1 in this study), a new set of daily acceleration and temperature data was collected. These data were processed using the same procedures as in the offline phase: the temperature was converted to a daily average, and the acceleration data were transformed into a new set of AR features through the extraction of the RD signature, followed by AR modeling. The previously trained XGBoost models were then loaded to predict the effect of temperature on the newly obtained AR feature vector, based on the current daily average temperature. This predicted effect was subtracted from the raw features, resulting in a temperature-compensated feature vector.

Anomaly scoring: The temperature-compensated feature vector for the new day is compared with the baseline mean vector and covariance matrix defined during the offline phase. This score quantifies how far the new data statistically deviates from the normal-condition distribution and is compared with the pre-defined WL.

Normal condition (MD < WL): If the MD score was below the WL, the bridge behavior is considered to be within the normal range. In this case, the data are classified as normal and can be added to the baseline dataset through feature augmentation. This allows the model to adapt gradually to minor changes that may occur over time, thereby improving its reliability. The system continues monitoring while awaiting data from the next day.

Anomalous condition (MD ≥ WL): If the MD score exceeds the WL, it is considered a potential anomaly. However, a single occurrence of an elevated MD score does not necessarily indicate structural damage. Such an increase may result from transient events, such as overloaded vehicle crossings, temporary sensor malfunctions, or unexpected environmental disturbances, collectively referred to as point anomalies. Therefore, event classification and validation procedures are required. For example, if the MD score continuously exceeds the WL for N consecutive days, the system classifies the situation as a "severe structural change" and issues an alert to the bridge administrator. In contrast, if the anomaly is non-recurrent, it is logged and managed as an isolated event but does not trigger an immediate structural warning. This multistep verification process is crucial in reducing false alarm rates and improving the practical reliability of the monitoring system.

5. Application and results

The proposed real-time structural health monitoring methodology was applied to the PSC-I bridge described in Section 2, and the monitoring results over a period of approximately 15 months are presented in Fig. 11. During the period defined as normal operating conditions, the bridge's vertical acceleration responses remained stable within a range of approximately ± 0.015 m/s^2. Throughout the monitoring period, 17 outliers were detected, with MD scores exceeding the WL. Notably, the two most prominent anomalies exhibited MD scores that were significantly higher than those of other anomalies. Analysis of the raw acceleration signals showed that these anomalies had amplitudes more than 20 times greater than those observed under normal conditions. These extreme responses are presumed to be caused by unusual traffic loading events, such as the passage of an overloaded vehicle or a convoy of vehicles traveling in close succession.

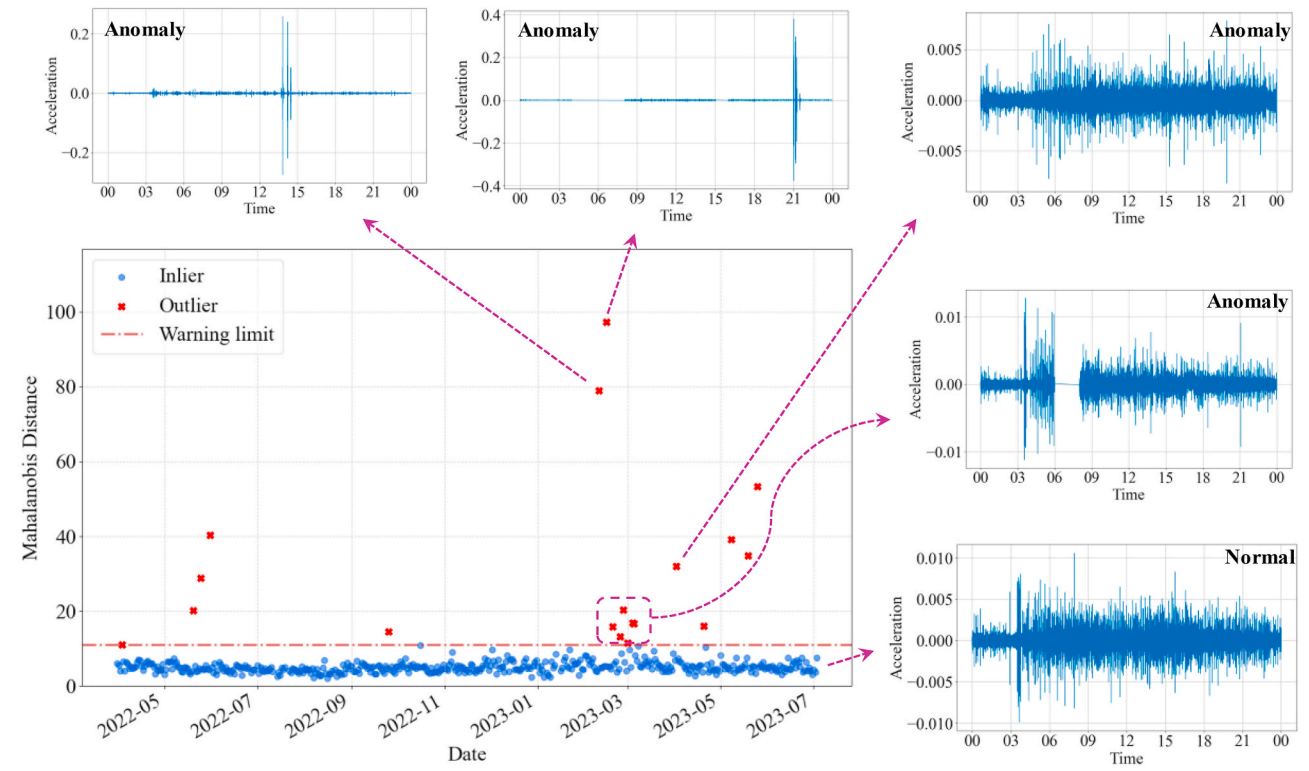
Notably, some anomalies detected near the warning threshold had acceleration amplitudes that were visually indistinguishable from those under normal conditions. This suggests that the proposed methodology is sensitive not only to the magnitude of the acceleration responses but also to subtle changes in the dynamic characteristics embedded within the signal. Further analysis revealed that these anomalies were closely linked to fluctuations in operational conditions, such as unusually high or low traffic volumes. Additionally, several anomalies coincided with periods of signal loss caused by temporary sensor malfunctions or data acquisition devices. Overall, all the detected anomalies were attributed to transient causes, including exceptional traffic loading, variations in operational conditions, or data acquisition errors. All detected point anomalies were followed by a return of the MD values to their normal baseline levels on the following day, indicating no evidence of permanent or accumulated structural damage and confirming that the system accurately classified these events as transient without generating false alarms.

To assess the generalizability of the proposed monitoring methodology, the same procedure was applied to bridges with STB, RCF, and RCS type bridges. The results are presented in Fig. 12. Regardless of bridge type, the MD values corresponding to normal condition data consistently ranged from approximately 0 to 12, indicating that no specific structural type significantly influenced the distribution of normal behavior. An analysis of the primary anomalies detected in each bridge revealed the following: for the STB, anomalies were attributed to noise-dominant responses caused by unusually low traffic volume, which reduced the signal-to-noise ratio. In the RCF and RCS bridges, anomalies were linked to signal loss due to temporary data acquisition failures. Similar to the PSC-I bridge, all anomalies in these structures were associated with atypical operational conditions or sensor system issues, with no evidence of persistent trends indicating structural degradation.

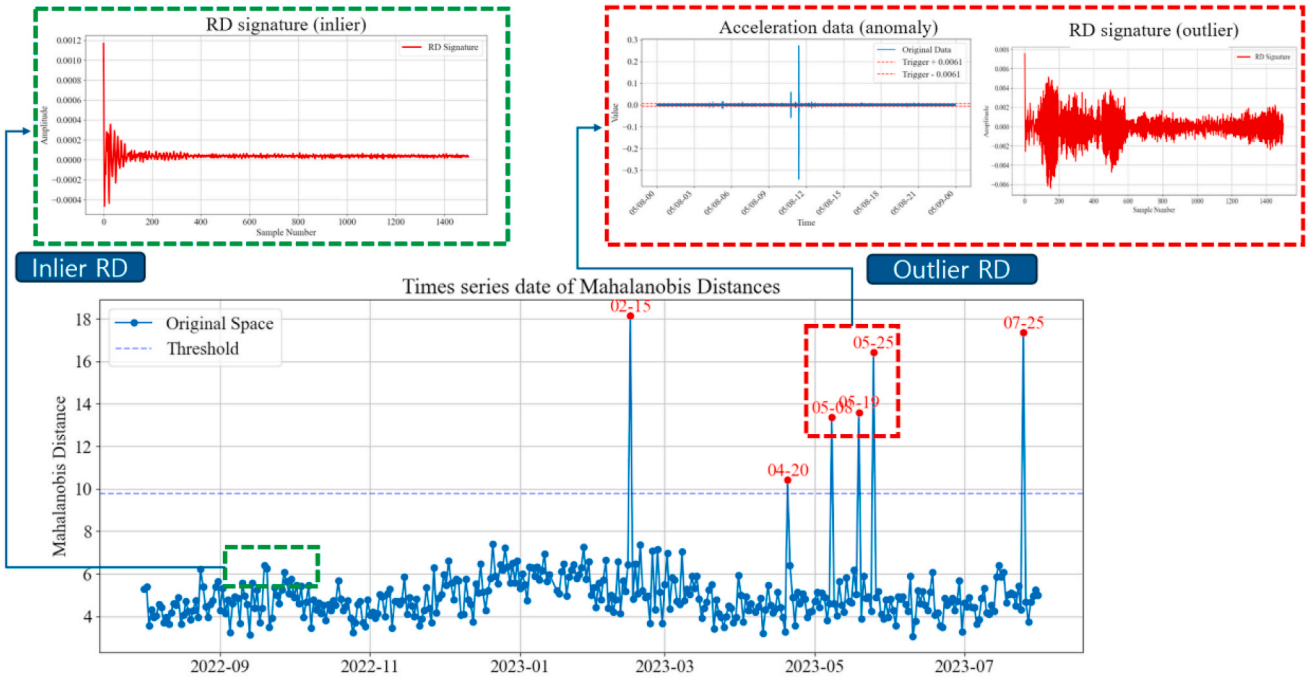
To verify whether the proposed methodology can detect actual structural changes beyond variations in operational conditions, a case study was conducted on an RCS bridge that underwent a change in pavement type (Fig. 13). During the initial monitoring period (July 2022 to July 2023), the bridge was covered with asphalt pavement. However, due to pavement deterioration, a complete replacement with higher stiffness concrete pavement was carried out in September 2024. Following the pavement replacement, the MD values showed a clear upward shift and formed a new cluster. In quantitative terms, the MD values under asphalt pavement exhibited a stable distribution with a mean of 5.2 and a standard deviation of 1.8. After replacement with concrete pavement, however, the mean increased to 11.5 with a standard deviation of 3.2, representing an approximately 121 % rise and forming a distinct cluster shift. This result indicates that the proposed methodology can sensitively detect subtle structural variations, such as changes in the global stiffness of the bridge. In such cases, where the bridge's normal condition permanently shifts, an operational strategy is necessary. This may involve redefining the baseline using post-replacement data or establishing a new warning limit (WL) at the discretion of the bridge manager.

6. Discussion and conclusion

This study proposes and validates a framework for unsupervised online monitoring of the global dynamic behavior of road bridges using a single accelerometer, enabling early detection of structural condition changes. The framework consists of four steps: (i) extraction of RD signatures from daily acceleration data, (ii) construction of daily feature vectors using the coefficients of an autoregressive (AR) model with an optimal order, (iii) correction of nonlinear temperature effects through XGBoost regression with daily mean temperature as input, and (iv) calculation of the MD against a reference Gaussian distribution defined by a robust MCD-based mean and covariance. Anomaly detection is conducted through a two-stage process comprising an offline (baseline establishment) and online (real-time evaluation) framework, where exceedance of the WL is used as the anomaly criterion. The WL is determined from the interquartile range of the MD distribution, and the

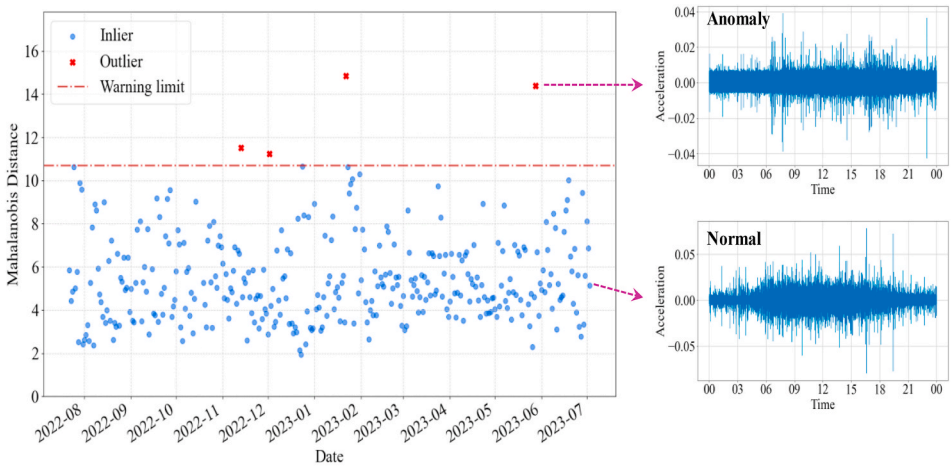


(a)

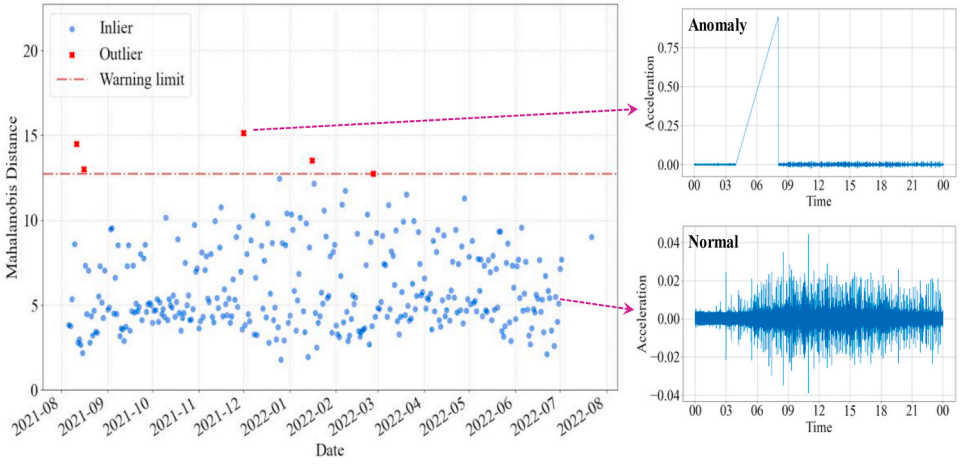


(b)

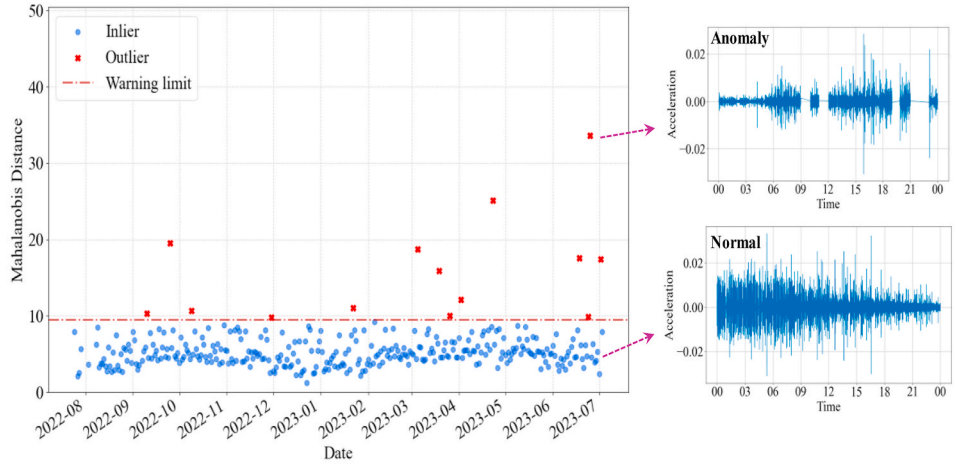
Fig. 11. Online monitoring result of a PSC-I bridge; (a) Relation between acceleration and Mahalanobis Distance, (b) Relation between Mahalanobis Distance and random decrement.



(a) STB bridge



(b) RCF bridge



(c) RCS bridge

Fig. 12. Online monitoring result of the other type bridges.

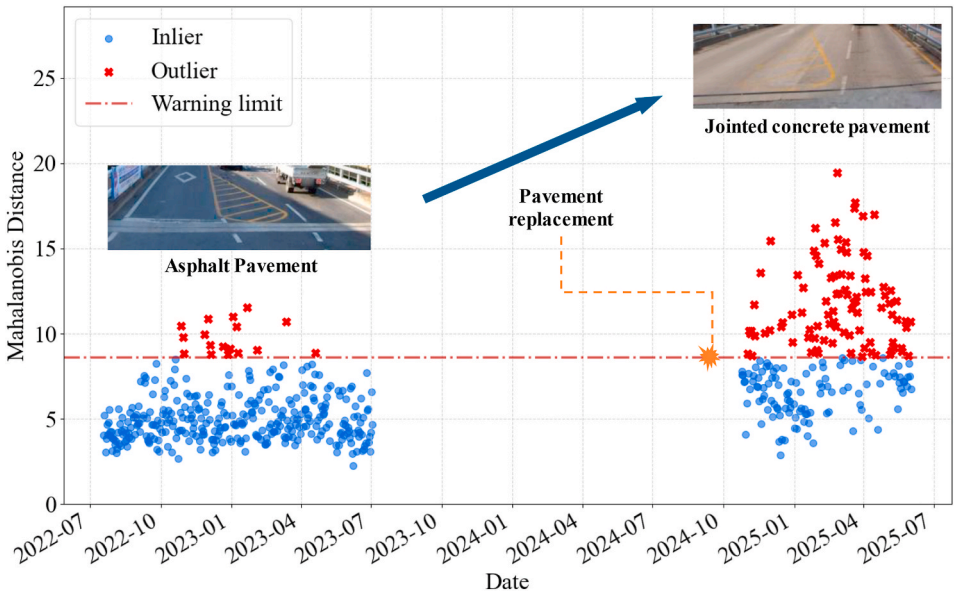


Fig. 13. Online monitoring result of another RCS bridge with pavement replacement.

sensitivity coefficient k is adjustable by bridge operators according to operational requirements.

When applied to four bridge types (PSC-I, STB, RCF, and RCS), the MD values under normal conditions generally remained within the range of 0–12. The major anomalies detected corresponded to operational or sensor-related issues, such as low traffic with low SNR conditions or temporary signal loss of the measurement device. These point anomalies immediately returned to the normal MD range on the following day, with no cumulative trends observed, indicating that the framework appropriately classified them as transient events without generating excessive alarms. No persistent signs of structural deterioration were identified.

In the case of pavement replacement on an in-service bridge, the MD values exhibited a stable distribution prior to replacement, with a mean of 5.2 and a standard deviation of 1.8. After replacement, however, the mean increased to 11.5 with a standard deviation of 3.2, representing an approximately 121 % rise and a clear upward cluster shift. This demonstrates that the proposed framework can sensitively capture structural changes, such as variations in global stiffness, even with a single sensor. In such cases where the normal state is permanently displaced, operational strategies such as redefining the baseline or resetting the WL using post-event data are required.

From an operational perspective, it was confirmed that at least one year of continuous data, including the winter season, is required. Capturing and modeling the natural variations in dynamic characteristics caused by seasonal and environmental factors (e.g., temperature) are essential for reliably distinguishing between normal and abnormal states. This study demonstrated such capability through daily windowing and temperature-compensation procedures. These findings provide practical guidance for data acquisition during the initial stage of long-term monitoring.

A practical limitation of this study is that the proposed system could not be directly compared with other real-time monitoring systems, as no such systems were installed on the target bridge. This constraint restricts the extent to which our results can be validated against existing approaches. Nevertheless, the proposed framework is designed as a cost-effective first-line screening tool for a wide range of ordinary bridges where expensive multi-sensor monitoring systems are not available. In particular, unlike conventional management practices that rely primarily on periodic visual inspections, the proposed method offers distinct advantages such as real-time anomaly detection and the potential for early identification of latent damage. These features highlight the system's practical value in enhancing maintenance efficiency and supporting more timely and informed decision-making in bridge management.

The key contributions of this study can be concluded as follows. An unsupervised online framework was formulated to enable continuous monitoring of road bridges using minimal sensing with a single accelerometer. A transparent and reproducible decision-making scheme was developed by integrating temperature compensation, robust baseline modeling, and statistical alarming. The framework's generalizability was demonstrated through applications to multiple bridge types with different structural forms, and its capability was quantitatively validated by detecting a cluster shift during a real structural change event, namely pavement replacement. Furthermore, operational guidelines were proposed for re-baselining or re-setting thresholds when permanent changes are identified.

Meanwhile, no major structural damage occurred during the monitoring period; thus, the MD evolution patterns associated with different damage types—such as sustained exceedance of the WL under abrupt damage, or gradual increases in mean and variance with higher near-threshold frequency under progressive damage—remain data-driven estimates. Accordingly, future research should generate diverse damage scenarios using FEM-based synthetic data to quantitatively assess sensitivity and robustness, and to standardize operational thresholding rules (e.g., continuous N days, retraining intervals) in terms of false alarm and missed detection rates. Furthermore, incorporating operational variables such as traffic volume, SNR, and missing data, along with advancing automatic baseline-resetting logic, will enhance the framework's applicability in broader field deployments.

Finally, the proposed framework offers practical advantages of low implementation cost and high scalability for agencies seeking to shift toward early warning and preventive maintenance strategies. The integrated procedure of data acquisition, correction, and decision-making ensures consistent quality of online monitoring across diverse bridge types and site conditions. Furthermore, the incorporation of dynamic re-baselining/threshold adjustment and simulation-based validation is expected to further enhance the practicality and reliability of single-sensor-based SHM.

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CRediT authorship contribution statement

Gitae Roh: Methodology, Visualization, Writing – original draft, Writing – review & editing. **Chi-Ho Jeon:** Data curation, Formal analysis, Methodology, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Ji-Heon Shin:** Data curation, Formal analysis, Investigation, Writing – original draft. **Chang-Su Shim:** Conceptualization, Supervision. **Byeongcheol Kim:** Data curation, Investigation, Project administration. **Jaehwan Kim:** Data curation, Investigation, Project administration. **Kyu-San Jung:** Data curation, Investigation, Project administration. **Ki-Tae Park:** Funding acquisition, Supervision.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Chi-Ho Jeon, Byeongcheol Kim, Jaehwan Kim, Kyu-San Jung, and Ki-Tae Park have patent pending to Korea Institute of Civil Engineering and Building Technology. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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