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Short-term damage alarming with limited vibration data in bridge structures: A fully non-parametric machine learning technique

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ABSTRACT

Machine learning-assisted vibration monitoring is an intelligent, automated, and popular strategy for evaluating civil structures and damage alarming. However, implementing this strategy under a short-term monitoring program may encounter challenges such as limited vibration data, profound environmental and operational variations, and the limitations of state-of-the-art solutions under these conditions. The main purpose of this paper is to propose a novel machine learning technique in terms of unsupervised learning for damage alarming with limited vibration data. The crux of this technique lies in two fully non-parametric parts of data partitioning and anomaly detection. Initially, a non-parametric clustering approach with a novel procedure is presented to divide limited vibration data into clusters. Subsequently, a new density-based anomaly detector is developed to prepare indicators for damage alarming. Limited eigenfrequencies of full-scale bridge structures are used to validate the proposed solution. Results can substantiate its effectiveness and practicability in short-term monitoring programs.

1. Introduction

Civil structures such as buildings, bridges, dams, etc. are critical and expensive assets of every society offering a range of services and benefits including shelter, transportation, and water and energy supply. These structures support the advancement and welfare of human societies by enabling economic development, social integration, environmental protection, and cultural diversity. However, natural and human-induced hazards always threaten safety, functionality, and sustainability of such structures causing unfavorable events and losses. Vibration-based structural health monitoring (SHM) is one of the practical and automated solutions for assessing civil structures. This methodology primarily involves continuous evaluation of a structure over time by measuring vibration and other influential parameters using different sensors [1–4], regular inspections of structural health and safety, and warning of the emergence of any adverse changes [5,6]. The implementation of a vibration-based SHM program needs several initial prerequisites including sensing systems for data acquisition, storage, and communication; engineering software for numerical modeling; feature extractors to derive useful information from measured vibration data; and computational methods for decision-making about the current status of the civil structure. Consequently, model-driven and data-driven techniques are key technical solutions employed in vibration-based SHM.

Depending on the strategic importance of the civil structure under monitoring, the main purpose of SHM, the type of structure and its geographical location, and total budgets, an SHM program can be carried out in short-term and long-term schemes. Short-term monitoring is typically implemented for a limited period to achieve specific objectives such as measuring and analyzing structural responses over extreme and sudden events (e.g., earthquakes, hurricanes, floods, fires, etc.), validating sensing systems and their functionalities, ensuring construction protocols align with design specifications, and recording new measurements after structural modifications such as retrofitting and rehabilitation. For such purposes, this program is often conducted over a few and limited days, weeks, or months [7]. In contrast, long-term monitoring is performed for a prolonged period, often spanning several years [8]. This program facilitates continuous measurements of various structural and environmental/operational data thereby enabling real-time analysis and in-depth understanding of structural behaviors.

Notwithstanding, the challenges and disadvantages associated with long-term SHM such as intractability and time-consuming nature of this

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process, high costs of sensor systems and installations, sensor malfunctions, the issues regarding Big Data and missing data, and high sensitivity of measured data to various unpredictable environmental and operational factors impede benefiting this monitoring program. Apart from these issues, one of the critical and dangerous problems of long-term vibration-based SHM is the delay in initially recording vibration data. This is particularly problematic during the first year of the measurement scheme when sufficient data should be collected to develop reliable computational models. This delay significant risks because there is no guarantee that the civil structure under inspection will operate normally without experiencing any damage or catastrophic events, which may occur during this period. To mitigate these challenges, an effective and cost-efficient solution is to divide an entire long-term program into manageable short-term strategies.

However, the short-term SHM has its own challenges and disadvantages. In contrast to the long-term monitoring, it can only provide limited information, complicating the development of robust machine learning models for SHM. Machine learning is a subfield of artificial intelligence that leverages various algorithms trained on different data to establish intelligent and automated models for conducting human-like tasks and solving complex problems [9]. A machine learning model is built using training data for various objectives such as anomaly detection, data clustering, prediction, and classification. This data may be fully labeled or completely unlabeled, leading to development of models under supervised or unsupervised learning categories, respectively [10].

In vibration-based SHM, unsupervised anomaly detection serves as the primary method for early damage assessment in civil structures. This approach only utilizes the vibration features of the undamaged structural state as unlabeled training data to develop a discriminative anomaly detector. Subsequently, new vibration features associated with the current or unknown state of the structure are inputted into this detector to identify any potential damage. Entezami et al. [11] proposed a non-parametric damage alarming technique based on the theory of empirical learning by concentrating on defining a new damage function through some empirical measures and the idea of minimized distance selection. Ma et al. [12] presented an unsupervised damage detector by enhancing a mixture of probabilistic principal component analysis (PCA) under multiple operational conditions with missing data samples. Entezami et al. [13] proposed a two-level double-hybrid learning technique compatible with unsupervised learning for damage alarming via modal frequency changes. The first stage of their method aimed at partitioning large feature samples (modal frequencies) and then a non-parametric damage function emanating from local outlier factor was developed to alarm the occurrence of damage. Zhang and Li [14] put forward a data-driven unsupervised damage diagnosis technique by using virtual impulse response function as an structural feature relevant to damage, time series modeling for feature extractor, and distance metric as a damage indicator function for anomaly detection. Ma et al. [15] introduced an unsupervised deep model based on variational autoencoder by considering raw acceleration time histories and a damage function. In their research, the variational auto-encoder, i.e., an unsupervised deep neural network, acted as a feature extractor so that its outputs in the damage function can perform anomaly detection. Despite such valuable research contributions, a significant issue in unsupervised damage assessment is the possibility that limited vibration data might not accurately determine the real status of the civil structure. Therefore, this necessitates the adoption of a robust and detailed unsupervised learning approach to overcome the limitations posed by limited vibration data in SHM.

On the other hand, an inevitable demanding issue in real-world SHM practices is the impacts of environmental and operational variability caused by air temperature, moisture, unpredictable wind flow, traffic, exceeding loadings, etc. on vibration data and also final decision-making reports [16]. Although these parameters might appear innocuous, changes in structural properties (i.e., mass and stiffness) and also structural responses induced by such conditions can mimic damage. Consequently, this can lead to false alarms or false positive errors, which are costly erroneous outcomes in SHM. Furthermore, these errors often necessitate redundant inspections and potentially unnecessary retrofitting thereby wasting both time and financial resources. Conversely, the intensity of changes stemming from the environmental and operational conditions may exceed those of certain minor and moderate damage patterns, potentially leading to mis-detections or false negative errors. Such oversights can have serious repercussions, posing a threat to human safety and potentially resulting in casualties. Although the impacts of environmental and operational variability often intensify during long-term monitoring, it has been observed that such conditions also influence the vibration features obtained from short-term monitoring [17]. The optimal resolution to these challenges lies in eliminating the impacts of environmental and operational parameters from structural responses and vibration features.

Recently, new approaches have been introduced to cope with the demanding issue of ambiguous decision-making resulting from the environmental and operational variability. Huang et al. [18] proposed a regime-switching cointegration approach to eliminating nonlinear environmental (i.e., temperature) influences from structural eigen-frequencies by extending the conventional Johansen cointegration to a nonlinear framework. In their work, PCA and Gaussian mixture model (GMM) were incorporated to obtain proper switching points. Prawin and Vijaya Bhaskara [19] combined the GMM with the Mahalanobis-squared distance (MSD) to detect anomalies in a lab-scale bridge model in the presence of environmental and operational variability, for which the GMM partitioned structural features influenced by such variability conditions in the same clusters by satisfying the same probability distribution. Santos et al. [20] improved the GMM-MSD technique for structural damage assessment under environmental and/or operational changes by integrating a standard Genetic algorithm and optimizing the initial parameters of the GMM estimated by the expectation–maximization approach. Sarmadi et al. [21] developed an unsupervised learning approach to normalizing vibration data through a novel hybrid feature weighting-selection algorithm relevant to the theory of statistical machine learning. Daneshvar et al. [22] introduced the theory of dictionary machine learning and developed a three-level approach that could reconstruct vibration data and also eradicate environmental and operational factors. Sarmadi et al. [17] proposed a novel probabilistic data self-clustering method for damage detection under the environmental and operational changes based on the principles of semi-parametric extreme value theory, local cluster assignment of any unlabeled feature, and an unsupervised feature selection through nearest neighbor search. Sarwar and Cantero [23] suggested a probabilistic temporal autoencoder for monitoring of bridge structures under variability cases. Their unsupervised deep learning model was capable of overcoming the environmental and operational impacts and detecting abnormal situations with the aid of an exponentially weighted moving average filter and a chart-based threshold mechanism. Roberts et al. [24] utilized regression-assisted data normalization by developing a nonlinear stepwise regressor to mitigate the nonlinear influences of environmental and operational conditions from vibration data of wind turbine blades. Lei et al. [25] suggested an autonomous detection of structural element damage subject to unknown seismic excitations by using a convolutional neural network with wavelet-based transmissibility of structural response data, for which the transmissibility functions of structural response data were considered to eliminate the influence of different seismic excitations.

Given these backgrounds, the removal of the environmental and operational conditions is often achieved by four main methodologies based on feature normalization, feature selection, feature clustering, and hybrid algorithms. Feature or data normalization is a widely-used solution that mainly changes the nature of data. By developing an unsupervised data normalizer with the capability of data reconstruction, it is possible to extract the residual between the original and reconstructed response data, which is then utilized as the normalized data/feature. The normalized features are then fed into an anomaly detector to determine the final SHM results, i.e., see the review article by Wang et al. [16]. Feature selection is a technique that involves disregarding irrelevant features, i.e., specifically those are sensitive to environmental and operational conditions, and retaining the relevant ones. The retained features are then used to develop an anomaly detector for decision-making. Feature clustering employs various data clustering methods to partition the original data into different sub-sets or clusters. Each cluster is then processed by an anomaly detector, and the minimum anomaly score across all clusters is chosen as the final output. Eventually, the hybrid algorithm integrates various aforementioned approaches to mitigate the effects of environmental and operational variations and to derive the final SHM results [8]. Within these categories, anomaly detectors can utilize state-of-the-art functions such as the widely-used MSD [19–21], or newly developed functions [11,13,17]. Despite novel solutions aimed at mitigating the challenge of the environmental/operational variability, most of them have been designed to overcome variability in large data. Given that the issue of variability in limited data has less been explored, this study primarily focuses on investigating this topic by proposing a novel solution.

On the other hand, the effectiveness and efficiency of machine learning methods are significantly influenced by their frameworks, which are typically categorized as non-parametric or parametric. Non-parametric methods do not require predefined unknown components, i.e., often referred to as hyperparameters, and do not rely on prior knowledge [11], whereas parametric methods depend on the estimation of these unknown components [26]. Because reliable estimation of such components significantly influences the overall performance of any parametric machine learning model, it is necessary to employ hyper-parameter optimization (HO) techniques for training the model of interest [27]. Although developing a robust non-parametric unsupervised learing method without prior labeled information and a predefined model structure may be challenging, its independence from influential hyperparameters enhances its adaptability to complex issues. Therefore, another key focus of this research is to leverage the concept of non-parametric machine learning to develop an effective and efficient approach to SHM with limited data and various variability patterns.

This paper proposes a fully non-parametric unsupervised learning technique for vibration-based SHM. Designed for early damage detection in civil structures, it requires only limited vibration data from a short-term monitoring program. The fundamental elements of this method are anchored in two pivotal aspects of unsupervised learning; that is, data clustering and anomaly detection. Accordingly, the proposed method comprises two steps including feature partitioning via a new clustering algorithm called *hierarchical information clustering* (HIC) and an innovative unsupervised function called here *density-based anomaly detector* (DAD). Employing a unique and innovative clustering strategy, the HIC automatically partitions limited vibration features (training data) regarding the undamaged state into distinct clusters. This partitioning significantly mitigates the confusing effects of environmental and operational variability on vibration features [8,28]. Using the clustered sets, test features associated with the current or unknown structural state as well as the initial training features are inputted into the proposed anomaly detector to determine their anomaly scores for damage assessment. In this regard, a non-parametric threshold estimator is also employed to keep the non-parametric nature of the proposed method.

The groundbreaking aspect of the proposed method lies in the non-parametric characteristics of both the feature partitioning and anomaly detection steps, obviating the need for additional hyperparameter optimization techniques to determine unknown components (hyper-parameters). The HIC algorithm can automatically identify sufficient clusters required for partitioning training data. This advantageous attribute implemented after final data clustering without prior knowledge makes it superior to many state-of-the-art clustering algorithms, which necessitate additional approaches to ascertain the optimal number of clusters as predetermined information (hyperparameter) and typically perform this step before final data clustering. Thus, one can realize that the HIC streamlines the entire clustering process. Conversely, the major advantage of the DAD method pertains to its structure, which is based on both density and distance characteristics. Additionally, it does not require prior determination of any unknown parameter emphasizing its non-parametric nature. The DAD algorithm offers a clearer interpretative framework for anomaly detection by leveraging the principles of dense and sparse sets, which make it practically user-friendly for detecting anomalies.

To validate the proposed method, two real-world bridge structures with limited vibration features (modal frequencies) are utilized. Both structures were subjected to different environmental and operational variations impacting on small sets of eigenfrequencies. Additionally, several comparative studies are conducted to demonstrate the superiority of the proposed method over some advanced and innovative techniques. Results indicate that the developed HIC-DAD successfully differentiates between undamaged and damaged conditions and effectively remove the influences of variations attributable to the environmental and operational conditions in short-term monitoring programs.

2. Proposed method

The proposed method comprises two main steps of data partitioning and anomaly detection for early damage alarming in short-term monitoring of civil structures. As previously discussed in Section 1, the methodological framework of the HIC-DAD for addressing the major challenges, especially the influences of the environmental/operational variability, relies on combining feature clustering and anomaly detection. This process begins with the HIC by partitioning the entire training samples into clusters. Subsequently, each cluster along with the training and test data is inputted into the DAD function to compute anomaly scores. In this regard, the minimum anomaly score across all clusters is selected as the final output for each training and test sample. The anomaly scores of the training data are then used to estimate a threshold for decision-making through a threshold estimator. If the anomaly score from any test sample surpasses this threshold, an alarm is triggered indicating damage and classifying the structure condition as damaged. Conversely, the score below the threshold indicates an undamaged state of the structure. For clarity, Fig. 1 illustrates the general flowchart of the proposed method. It should be noted that threshold estimation is an inevitable part of any unsupervised anomaly detection that plays an important role in decision-making. To keep the non-parametric nature of the proposed method, a non-parametric threshold estimator based on a statistical confidence interval (SCI) is considered to determine a user-friendly threshold boundary without any complexity.

2.1. Hierarchical information clustering

The HIC is an unsupervised data partitioning technique that introduces a graph-theoretic strategy for extracting clusters and hierarchies in unlabeled sampling data without any prior information [29]. One of the key advantages of the HIC is its non-parametric nature. This characteristic is particularly advantageous because it circumvents the need for pre-determining the number of clusters, which is a common requirement and hyperparameter in most data clustering techniques. The other advantage of the HIC is its aptitude for partitioning data that contains latent information [29]. In the context of SHM, such latent information typically includes different variability patterns in structural modal frequencies.

The non-parametric clustering framework and graph-theoretic strategy of the HIC is provided by constructing topologically embedded networks, which consist of sets of most relevant links analyzing the network structure. The HIC delineates two kinds of hierarchy classes for planar embedding: (1) the inside-cluster hierarchy,

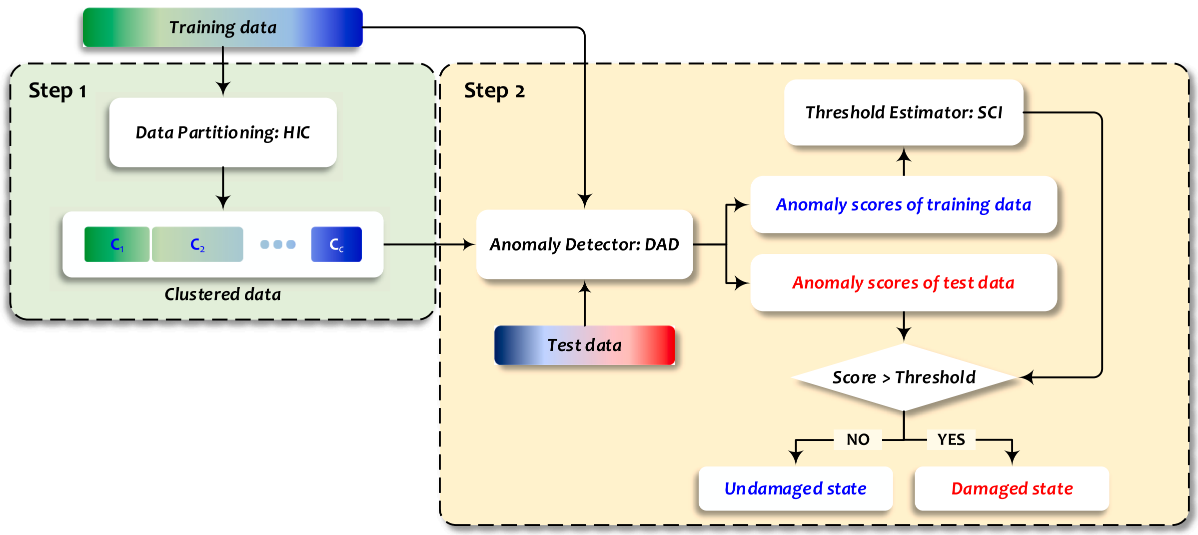

Fig. 1. Flowchart of the proposed HIC-DAD method for early damage alarming.

which illustrates how clusters are composed of smaller units, and (2) the between-cluster hierarchy, which shows how clusters are interconnected or merge with each other. For these procedures, a graph with restricted complexity must be constructed by a deterministic process, which repeatedly integrates the most pertinent connections. The graph is embedded on a hyperbolic surface of genus, which limits the construction. The genus denotes the quantity of handles or perforations on a surface. For example, a sphere is a planner graph with the genus zero, while a torus has genus 1. Moreover, it is worth remarking that a graph is a structure of data with the collection of objects (i.e., nodes or vertices) along with a set of interactions (i.e., edges or links) [30]. On the other hand, the embedding process refers to the transformation of graphs into a vector or a set of vectors, which facilitate representing the graph structure, detailing the connections between vertices, and capturing essential information about the graph, its elements and vertices. With these preliminary descriptions, the HIC exploits a Planner Maximally Filtered Graph (PMFG), which can split a topological sphere into triangles. Indeed, it is a weighted graph with weights and similarities between edges and vertices. Accordingly, the HIC employs the simplest graph style with genus zero. It is pertinent to mention that topologically embedded graphs on planner surfaces with the genus zero contain a relatively small number of edges or links, making them well-suited for datasets with limited but significant latent information [29].

The HIC utilizes the structure or shape of the PMFG to discover data characteristics. Within this framework, a hierarchy (designated as G) is developed based on planarity, resulting in either separating or non-separating cyclic paths. Accordingly, two subgraphs emerge: one separated by vertices linked to a cyclic path and another non-empty subgraph. The PMFG primarily uses the simplest cyclic path, i.e., called here the triangular cluster, to divide G into two disconnected parts, termed the inside (G_{in}) and outside (G_{ex}) subgraphs, which remain linked through shared vertices. This division continues until all triangle clusters splitting G are utilized. The final structure, a collection of planar graphs termed *triangular bubbles*, connects through the triangle cluster, forming a *triangular bubble tree*. This tree ultimately represents a graph with vertices indicating triangular bubbles and edges referring to the clusters. Each edge is associated with a path, determined by summing the edge weights within the PMFG that connect the triangular set to two bubbles.

To make it simple, Fig. 2 depicts how to build a triangular bubble tree, where the PMFG contains nine vertices (i.e., $v_1,\ldots,v_9$), three triangular clusters (i.e., h_1, h_2, and h_3), and four triangular bubbles (i.e., $b_1,\ldots,b_4$). Mathematically, the edge between the i^{th} and j^{th} bubbles (b_i and b_j) is defined by comparing the connections of the k^{th} triangular cluster (h_k) with the internal and external sub-graphs as follows:

$$W_k = \sum_{b_i \in h_k, b_j \in G_{in}, G_{ex}} A(b_i, b_j), \tag{1}$$

where $A(b_i,b_j)$ is the element at the intersection of the i^{th} row and j^{th} column members of the graph adjacency matrix, detailing the connections of h_k. In this scenario, the edge orientation is determined by the direction with the highest weight. Based on these principles, the HIC differently constructs *converging*, *diverging*, and *passage* bubbles. In the first bubble type, all linked edges converge into the bubble, while the second type is characterized by edges that leave the bubble. The third type features both incoming and outgoing edges. Among them, converging bubbles are crucial as they are the endpoints of directed paths with the maximum links, making them central to the clusters in the HIC. More precisely, any bubble connected through a directed path to a converging bubble, b_c, is classified as a member of the cluster c.

The bubbles within cluster c form a smaller tree t_c centered around a single converging bubble, i.e., b_c, to which all edges are connected. This setup facilitates a clustering process for the vertices of the hierarchy G, designated as $\mathbf{v}_G$. To achieve distinct clustering, each vertex b is assigned to the nearest bubble, defined by the shortest distance. Initially, vertices that belong to the same converging bubble are connected. For vertices associated with more than one converging bubble, connections are determined based on a measure known as the strength of attachment, detailed as follows:

$$\Delta(b_i, b_c) = \frac{\sum_{b_j \in \mathbf{v}(b_c)} A(b_i, b_j)}{3(N-2)}, \tag{2}$$

where N and $3(N\text{-}2)$ denote the vertex and edge numbers of b_c, respectively. For the mentioned vertices, the attachment occurs to the converging bubble with the largest Δ value. Subsequent to this allocation, each converging bubble encompasses a distinct collection of vertices. Regarding the vertices irrelevant to the converging bubbles, which are linked to the subtrees, those are assigned to these bubbles by computing their minimum average shortest path distance as follows:

$$\Pi(b_i, b_c) = \mathrm{Avg}\left(L(b_i, b_j) | b_j \in \mathbf{v}(b_c) \wedge b_i \in t_c\right), \tag{3}$$

where $L(b_i,b_j)$ stands for the shortest path distance (i.e., the smallest sum of distances) on G from b_i to b_j. With these details, one can determine a distinct division of the vertex collection of G into various vertex subsets, each connected to discrete clusters or their respective converging bubbles.

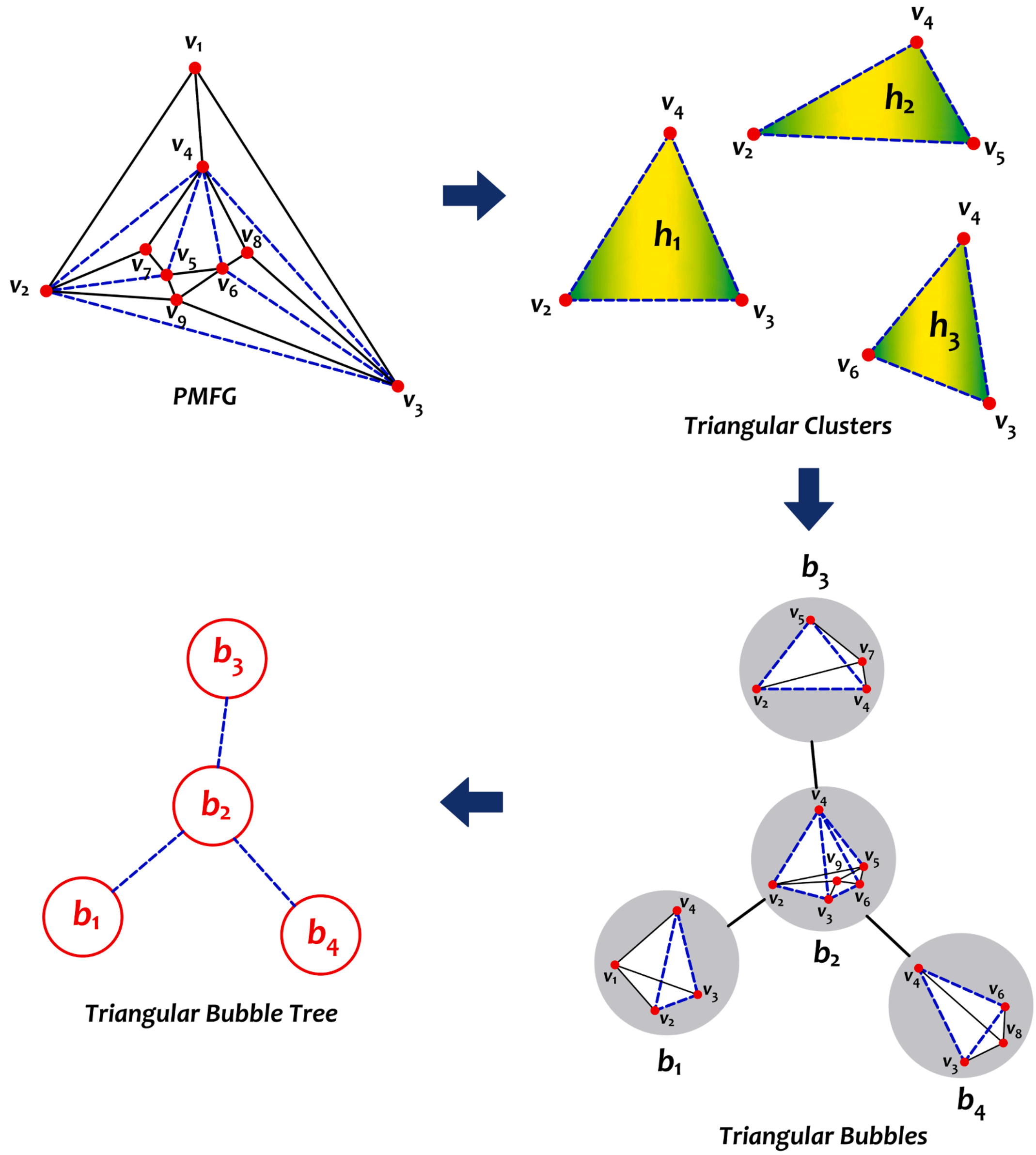

Fig. 2. Graphical representation of generating a triangular bubble tree.

After partitioning the vertex set into discrete clusters, two key processes should be evaluated: the internal organization within each cluster and the aggregation of clusters into larger forms, facilitated by a tailored linkage strategy, which can construct intra-bubble, intra-cluster, and inter-cluster hierarchy levels [29]. From this framework, a novel linkage emerges that connects discrete clusters into superclusters at the higher level and subdividing them into a hierarchy of bubbles and elements at the lower level. Therefore, the aforementioned procedures enable the HIC to automatically partition data in different clusters without any prior information, especially the number of clusters. In essence, the HIC automatically identifies the requisite number of clusters upon completing data partitioning. This represents its significant advantage over state-of-the-art clustering techniques, which require predetermined optimal cluster numbers before beginning the clustering process.

Given the training data $\mathbf{X} = [\mathbf{x}_1,\dots,\mathbf{x}_n]$, which represents the n vibration features regarding the undamaged structure, the output of the HIC is a set of c clusters $\{\mathbf{C}_1,\dots,\mathbf{C}_c\}$. Each feature vector consists of p variables, which represent the modal frequencies of p modes. Moreover, each cluster is a matrix comprised of p variables (rows) and n_c observations or samples (columns).

2.2. Density-based anomaly detector

The principal essence of the proposed damage alarming method stems from the idea of unsupervised anomaly detection and the inverse relationship between the density and distance of a data sample. Generally, a dense area contains closely spaced samples, characterized by high densities and short distances, in contrast to a sparse area, where samples exhibit low densities and greater distances. The proposed unsupervised method, termed the Density-Based Anomaly Detector (DAD), presents a framework for alerting to anomalies based on the densities and distances of data samples. It generates a dense set of normal features representing undamaged structural states. Because these features are closely related, the set is characterized by high density and short distances between samples. When an anomaly occurs or a feature sample associated with a damaged state emerges, the densities between samples increase or the distances decrease. In this scenario, the dense set transitions to a sparse one. To put it another way, as the properties of anomalies differ from the normal samples, the sparse set is characterized by small densities and large distances between the samples. In essence, this is the rationale behind the proposed DAD method, which is somehow depicted in Fig. 3.

Reconsidering the training data $\mathbf{X} = [\mathbf{x}_1,\ldots,\mathbf{x}_n]$ indicating the features of the undamaged structure, the density value of the i^{th} sample is expressed as follows:

$$\widehat{\rho}(\mathbf{x}_i) = \frac{d(\mathbf{x}_i)}{\sum_{k=1}^{n} d(\mathbf{x}_k)} \tag{4}$$

where the notion d refers to a distance function. Since the training data is a matrix, the Mahalanobis-squared distance (MSD) is the most choice for data density calculation. Accordingly, Eq. (4) can be rewritten as follows:

$$\widehat{\rho}(\mathbf{x}_i) = \frac{(\mathbf{x}_i - \boldsymbol{\mu}_x)^T \mathbf{H}_x^{-1} (\mathbf{x}_i - \boldsymbol{\mu}_x)}{\sum_{k=1}^{n} \left((\mathbf{x}_k - \boldsymbol{\mu}_x)^T \mathbf{H}_x^{-1} (\mathbf{x}_k - \boldsymbol{\mu}_x) \right)} \tag{5}$$

where $\boldsymbol{\mu}_x$ and $\mathbf{H}_x$ represent the mean vector and covariance matrix of $\mathbf{X}$. An important note is that Eq. (5) determine the global density value of $\mathbf{x}_i$. Based on the first step of the proposed method, the HIC splits the whole training data into c local subsets $\{\mathbf{C}_1,\ldots,\mathbf{C}_c\}$. Because the training set contains the undamaged feature samples of a civil structure and it is expected that such samples make a dense area, the maximum value among all c density quantities related to the c local subsets is chosen as the final density value. Hence, the local density value of $\mathbf{x}_i$ is expressed as follows:

$$\rho(\mathbf{x}_i) = \max\left(\frac{\left(\mathbf{x}_i - \boldsymbol{\mu}_j\right)^T \mathbf{C}_j^{-1} \left(\mathbf{x}_i - \boldsymbol{\mu}_j\right)}{\sum_{k=1}^{n_{c_j}} \left(\left(\mathbf{x}_k - \boldsymbol{\mu}_j\right)^T \mathbf{C}_j^{-1} \left(\mathbf{x}_k - \boldsymbol{\mu}_j\right) \right)} \right) \tag{6}$$

where n_{c_j} signifies the instance number of $\mathbf{C}_j$ and $j = 1,\ldots,c$. Although the local data density can be used as an anomaly indicator, in which case a small density value can be indicative of an anomaly, it is better to convert Eq. (6) into a distance function. The major merit of this conversion is the possibility of applying further threshold estimators for final decision-making. Due to the reverse relationship between the density and distance, the definition of the distance function for anomaly detection is simply derived by inverting Eq. (6) in the following form:

$$\delta(\mathbf{x}_i) = \frac{1}{\rho(\mathbf{x}_i)} \tag{7}$$

Using Eq. (7), it is feasible to determine n anomaly scores or damage indicators$\{\delta(\mathbf{x}_1),\ldots,\delta(\mathbf{x}_n)\}$ concerning the undamaged training instants. These scores are then adopted to set a warning threshold. Using the SCI-based threshold estimator, which offers a non-parametric approach under the central limit theorem, the threshold boundary is determined by the following function, which computes the mean (m_{Tr}) and standard deviation (s_{Tr}) of the anomaly scores of the training samples:

$$\tau_{(\alpha)} = m_{Tr} + \zeta_{(\alpha)} s_{Tr} \tag{8}$$

where α denotes the significance level and $\zeta_{(\alpha)}$ is the (1–α) critical value of the anomaly scores of the training data [13].

Now, let us assume that $\mathbf{z}_l$ is the l^{th} unknown test feature sample regarding the current structural state, where $l = 1,\ldots,m$. To determine the anomaly score of this sample $\delta(\mathbf{z}_l)$, it only suffices to replace $\mathbf{z}_l$ with $\mathbf{x}_i$ in Eqs. (6) and (7). If $\delta(\mathbf{z}_l)$ surpasses the threshold, one should expect that the technique alerts the presence of damage; if not, it declares that the structure still keeps its undamaged format.

3. Applications

3.1. Simulated short-term monitoring of a concrete box-girder bridge

This structure called the Z24 Bridge [31] was a classical post-tensioned concrete box-girder bridge with a primary span length of 30 m and two side spans of 14 m as shown in Fig. 4. This bridge was suited in the canton Bern, Switzerland and it was a part of the road connections between Koppigen and Utzenstorf overpassing the A1 highway between Bern and Zurich. Each bridge abutment had three columns joined with the main girder and the bridge piers were fixed into the girder. Because a new railway adjacent to the highway needed a new bridge with a greater side span, it was decided to destroy the Z24 Bridge in 1998.

During the year before the bridge destruction, a long-term monitoring program was conducted to measure the bridge dynamic responses in terms of acceleration time histories and some environmental factors such as temperature, relative humidity, rain, wind speed, and wind direction. The dynamic responses were measured via accelerometers installed in the bridge deck and five different sensors were considered to record environmental data. Due to the importance of thermal effects on the bridge behavior, a dense network of temperature sensors was installed at nine points on the bridge girder. Apart from the long-term monitoring program, progressive damage tests were incorporated into the Z24 Bridge in order to measure bridge responses under different damage scenarios. This program was performed shortly before the

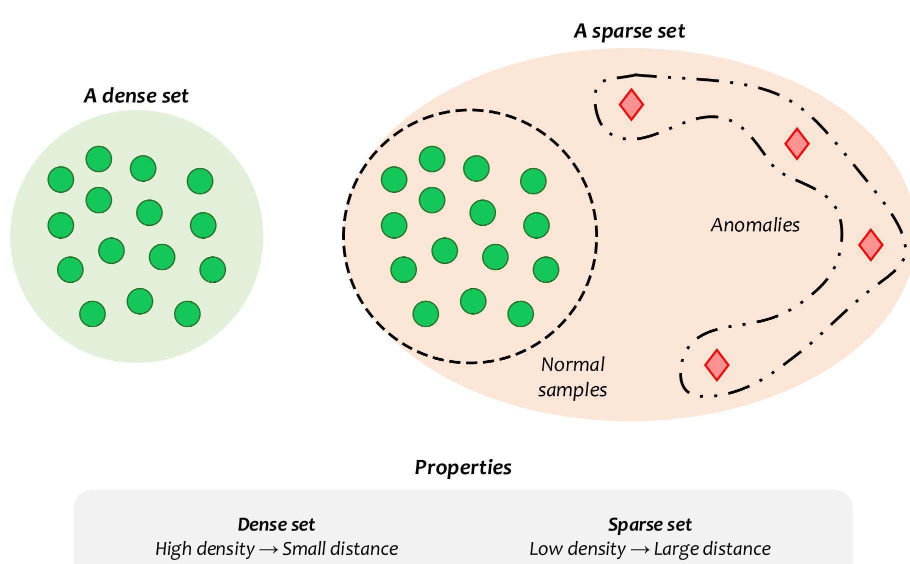

Fig. 3. Schematic illustration of the key principles of the DAD method.

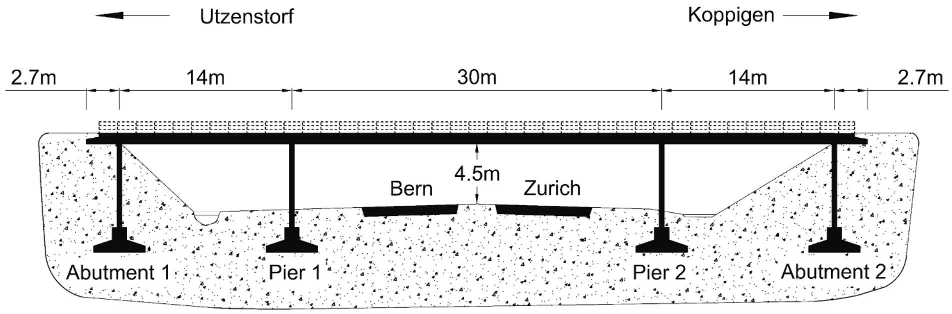

Fig. 4. The concrete box-girder bridge (i.e., the Z24 Bridge).

complete destruction of the bridge. These scenarios were realistic with frequent occurrences in concrete bridge structures.

The bridge modal frequencies in four stable modes ($p = 4$) were identified by an operational modal analysis (OMA) technique [31]. Despite the long-term monitoring program of the Z24 Bridge between 1997–1998, limited data in daily measurements concerning the undamaged and damaged conditions is considered to simulate a short-term monitoring scheme [32]. Accordingly, a few eigenfrequencies are used as the vibration data related to the simulated short-term monitoring. This set is comprised of 235 frequency samples so that the samples 1–198 relate to the undamaged state and the remaining ones (i.e., the samples 199–235) belong to the damaged state as shown in Fig. 5

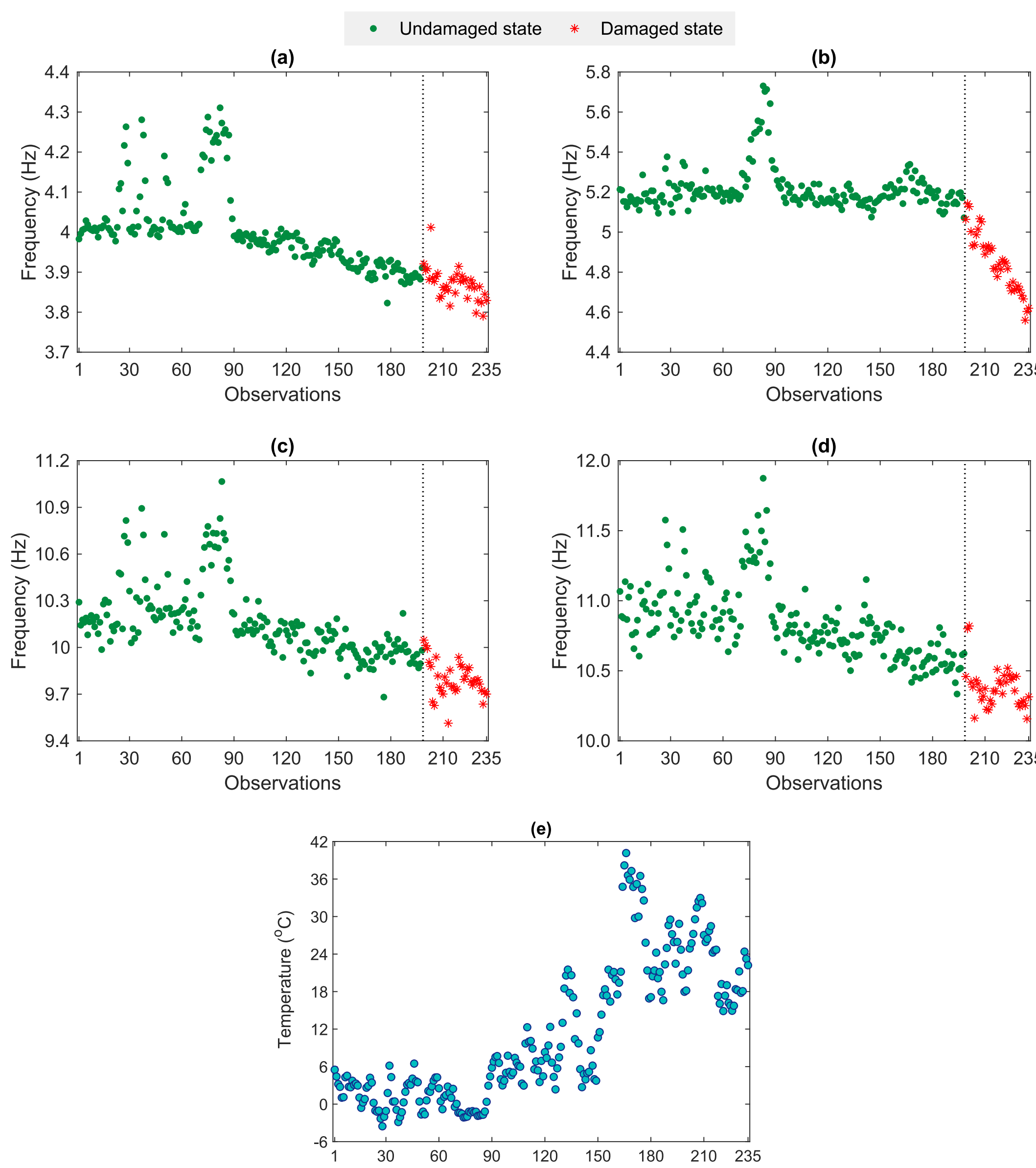

Fig. 5. Short-term eigenfrequencies of the box-girder bridge regarding the first-forth modes (a)-(d) along with the corresponding temperature records (e).

(a)-(d). Moreover, Fig. 5(e) illustrates the temperature records during the simulated short-term monitoring. Variability in the undamaged eigenfrequencies is clearly evident, emerging as sudden increases. This type of variability is concerned with the impact of cold weather so that the freezing temperature stiffened the asphalt of the bridge deck and increased the bridge stiffness. The other variation is related to the reduction of the modal frequencies when the progressive damage scenarios were induced. With such characteristics, the proposed method is tested in two key aspects: (1) its ability to overcome temperature variability, and (2) its effectiveness in correctly alarming the occurrence of damage using limited data.

To benchmark HIC-DAD, it is required to specify the training and test instances. Following this purpose, 80 % of undamaged eigenfrequencies from all four modes is utilized to have a training matrix of 158 instances ($n = 158$), while the remaining 20 % of the undamaged eigenfrequencies is considered as the validation or known test points. Merging such points with all frequencies of the damaged state (i.e., unknown test points), a test matrix with 77 samples ($m = 77$) is generated. Subsequently, the first part of the proposed method, i.e., feature partitioning, begins by using the HIC to split the training matrix into c clusters. According to the descriptions mentioned in Section 2.1, Fig. 6(a) and (b) display the adjacency matrix and PMFG of the training points. Moreover, Fig. 7 depicts the shortest path distances of the training data. Using such details, the HIC makes a hierarchical binary cluster tree (linkage) to automatically determine of the number of clusters. Fig. 8(a) indicates the generated linkage of the HIC method, where $c = 16$. Thus, the undamaged training instances in $\mathbf{X}$ are split into $\{\mathbf{C}_1,\ldots,\mathbf{C}_{16}\}$. The cluster label of each training sample is shown in Fig. 8(b).

It should be clarified that the HIC algorithm could produce reasonable partitions of the limited training data without any empty cluster, which is a big challenge in data clustering [33: Chapter 9]. It occurs when no data points are assigned to a particular cluster, in which case the cluster of interest contains zero member. From Fig. 8(b), it is clear that all clusters have sufficient samples. The other important note about the performance of the HIC is related to the dimensions of clusters that play significant roles in estimating covariance matrices for applying to the DAD function. As explained, the HIC partitions the entire training data into c clusters containing p variables and different cluster sample numbers (n_c). In statistics, if the number of samples of a matrix is smaller than the number of variables, the covariance matrix may be problematic and unreliable [34]. To reliably estimate the covariance matrix of a cluster, hence, the number of clustered samples should be at least equal to the number of variables. In Fig. 8(b), the minimum number of clustered samples corresponds to 4, satisfying this requirement. Therefore,

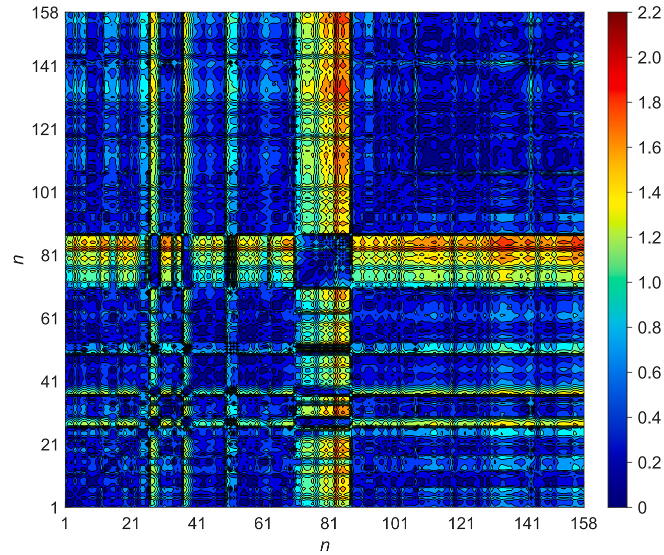

Fig. 7. The shortest path distances of the training points regarding the box-girder bridge.

the clarifications prove that the proposed HIC algorithm can provide reasonable clusters.

Having considered the training and test features as well as the clusters $\{\mathbf{C}_1,\ldots,\mathbf{C}_{16}\}$, Fig. 9 illustrates the result of early damage alarming in the box-girder bridge by the proposed HIC-DAD method along with the SCI-based threshold estimator under a 1 % significance level (i.e., a 99 % confidence interval). To ensure that no false alarm has occurred, a detailed plot of anomaly scores of some training samples close to the threshold line is also plotted. Regarding the choice of significance level or confidence interval, it is important to note that one of the primary objectives of the proposed method is to mitigate the negative impacts of variability patterns. Therefore, it is reasonable to apply a small significance level [8,22]. Furthermore, the rationale for selecting the 1 % significance level stems from its common use in statistical practice when a high level of confidence in the results is desired. In particular, by setting the significance level at 1 %, the likelihood of incorrectly flagging a normal data point as an anomaly is reduced to only 1 %, thereby effectively minimizing the false positive rate. This selection also prevents the degradation of the performance of the proposed method that could occur with a higher significance level, which

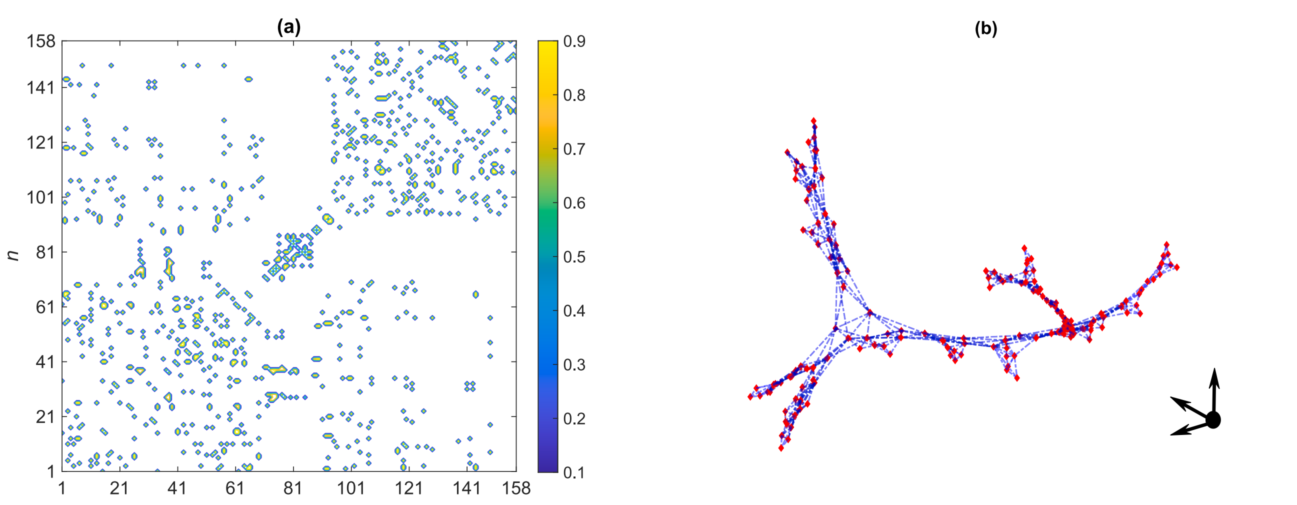

Fig. 6. The undirect graph construction based on the HIC algorithm related to the box-girder bridge indicating the adjacency matrix (a) and PMFG (b) of the training instances.

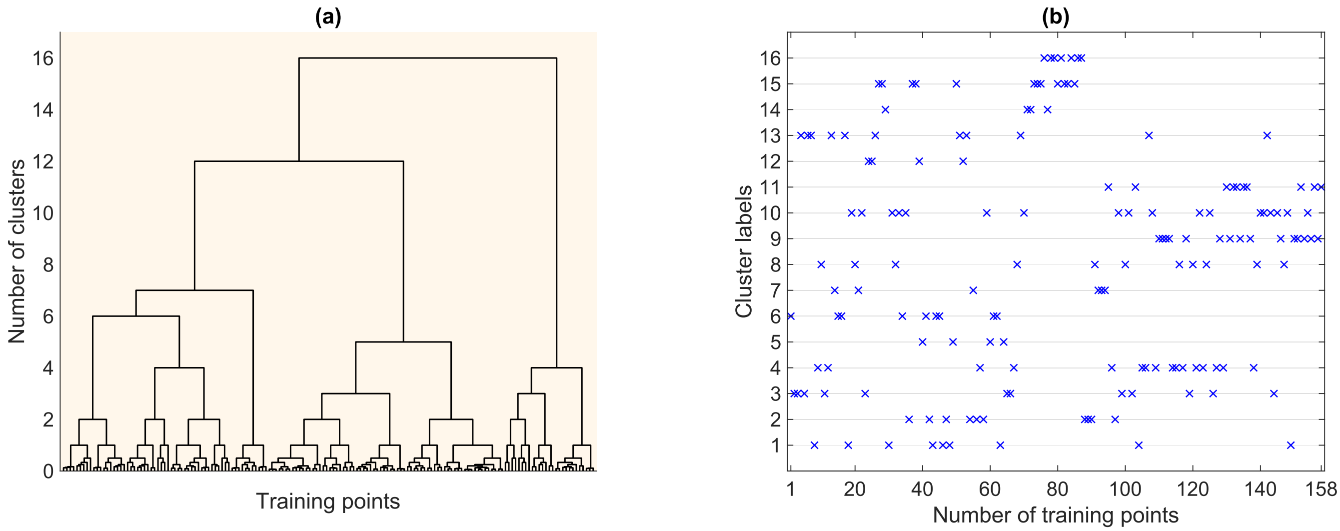

Fig. 8. More details of the HIC regarding the concrete box-girder bridge including the hierarchical binary cluster tree (a) and cluster labels (b) of the training instances.

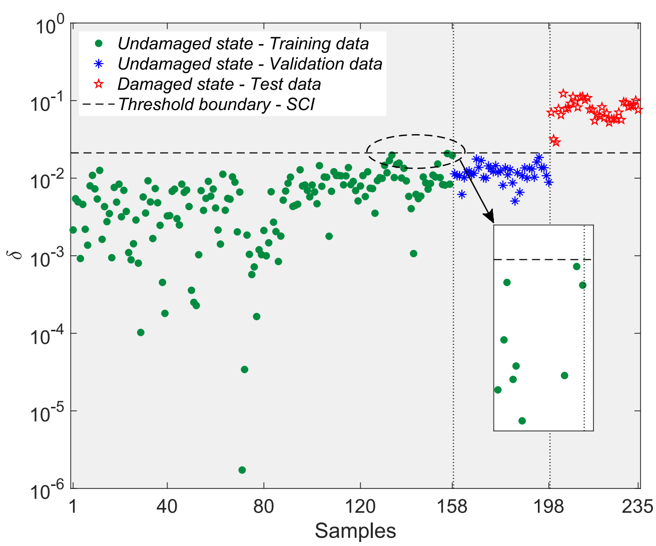

Fig. 9. Early damage alarming in the box-girder bridge by the proposed HIC-DAD method.

might incorrectly suggest that the method is unable to address the effects of environmental and operational variability, despite being well-equipped to handle these challenges. From Fig. 9, it can be observed that the anomaly scores of the undamaged state do not correctly exceed the threshold line, while the damaged anomaly indices are over the threshold. These conclusions clearly demonstrate the efficiency of the HIC-DAD in detecting the presence of damage without any false alarms or mis-detection errors. A notable observation from Fig. 9 is that the sudden increases in the undamaged eigenfrequencies do not influence on the final outcome.

To showcase the success and reliability of the HIC-DAD, it is benchmarked against techniques within the realm of non-parametric unsupervised learning. The first approach is the well-known MSD, which is still a commonly-used technique for SHM of different civil structures [21,35,36]. For the second comparison, it is attempted to evaluate the absence of the HIC or feature partitioning on the proposed method. In other words, the entire features are used in the DAD instead of local information or clustered data. Fig. 10 shows the results of the mentioned comparisons, where the dashed horizontal lines indicate the thresholds obtained from the SCI approach. It should be noted that the same 1 % significance level as the proposed method is applied to ensure fair comparisons. A clear observation in Fig. 10 is the inabilities of the MSD and DAD to discriminate the damaged state from the undamaged one even without the threshold boundaries. To put it another way, there are overlaps in the anomaly scores of the undamaged and damaged states, which indicate poor damage detectability of the MSD and DAD. The main reasons for this performance pertain to the influence of environmental variability and the use of entire training data for applying to the MSD and DAD function. Accordingly, considerable mis-detection (false negative) errors do not allow these approaches to correctly alarm the occurrence of damage. In contrast to the proposed HIC-DAD method, which exhibits zero false alarm and mis-detection errors, the MSD and DAD techniques encounter the mis-detection rates of 83.78 % and 75.67 %, respectively, along with the false alarm rate of 1.51 %. The outcomes of these comparative analyses clearly demonstrate the positive effect of feature partitioning and local information provided by the HIC to mitigate the negative impact of the environmental variability occurred in the box-girder bridge.

The other comparison is conducted to indicate the effectiveness of the HIC-DAD method compared to its counterpart. Since the proposed method consists of two parts, i.e., data clustering and anomaly detection, it is benchmarked against the well-known GMM-MSD technique. Initially, the GMM partitions the entire training data into predetermined clusters or components (designated here as $\hat{c}$). Subsequently, the mean vectors and covariance matrices for all clusters are calculated and utilized in the MSD function. Finally, the training and test feature samples are inputted into this function, and the minimum distance value among all clusters for each feature is selected as the final anomaly score. In contrast to the proposed HIC method, the GMM is a parametric clustering algorithm, which needs to determine the number of components ($\hat{c}$) before final data partitioning. Bayesian information criterion (BIC) is one of the commonly-used techniques. Using some sample components, the optimal component is one that yields the minimum BIC value [22]. Fig. 11(a) indicates the BIC quantities of 10 sample components, where the best choice belongs to the second component ($\hat{c} = 2$). The result of early damage assessment by the GMM-MSD is shown in Fig. 11(b) using the same SCI-based threshold estimator under the 1 % significance level. While the GMM-MSD surpasses the MSD and DAD in enhancing damage detectability, its susceptibility to false alarms, especially in the validation data, and the emergence of some mis-detection errors diminish its overall effectiveness compared to the proposed method. The other advantage of the HIC-DAD over the GMM-MSD is its non-parametric

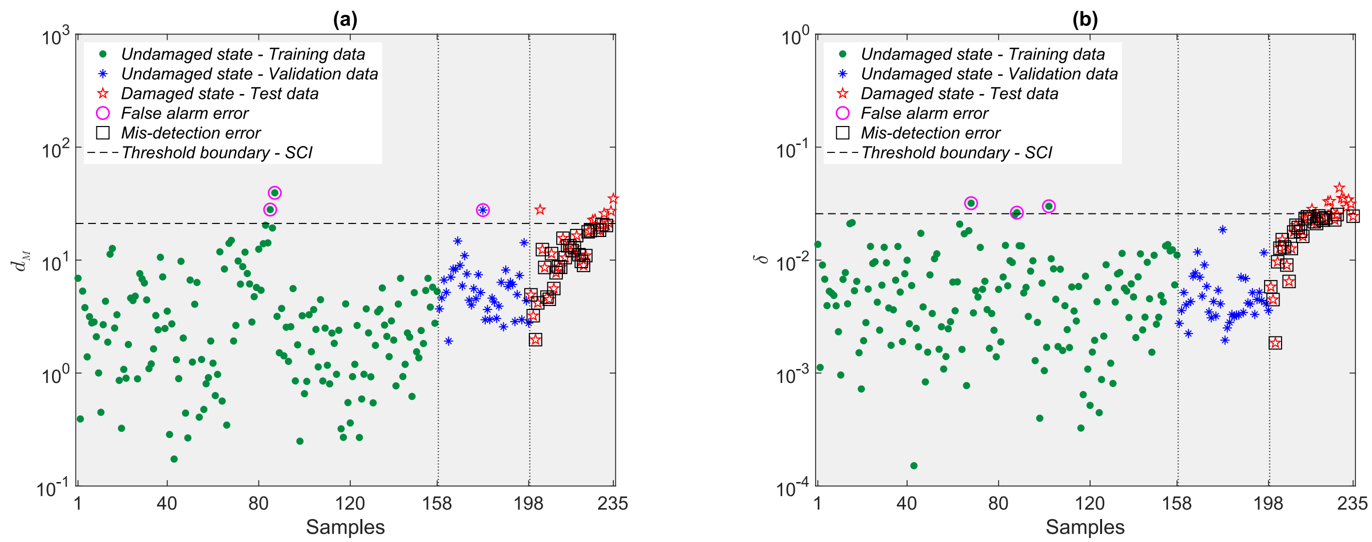

Fig. 10. Early damage alarming in the box-girder bridge: (a) MSD, (b) DAD.

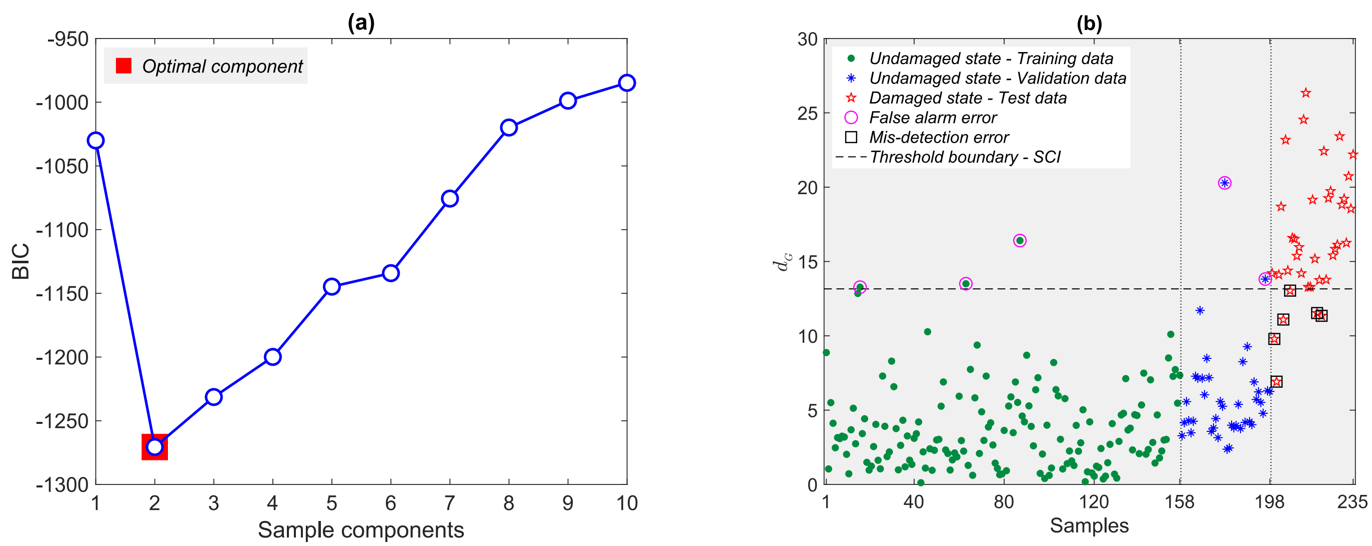

Fig. 11. Early damage alarming in the concrete box-girder bridge by the GMM-MSD including selection of the optimal component number using the BIC (a) and evolution of anomaly scores (b).

approach to data partitioning, which indicates its efficiency compared with the state-of-the-art GMM-MSD.

The final comparison assesses the complexity of the proposed HIC-DAD method against recent unsupervised learning techniques, called here NP-EML [11], NP-IAD [37], GDM [22] and MTUL [28]. These techniques address similar challenges as the proposed method, except they do not specifically tackle the scenarios involving limited vibration data. In this regard, NP-EML and NP-IAD exclusively introduce non-parametric anomaly detectors, while GDM and MTUL integrate feature partitioning through a variety of parametric clustering algorithms (i.e., GMM and spectral clustering) with different unsupervised anomaly detectors. Given that the aforementioned techniques yield promising results in early damage alarming without false alarm or mis-detection errors, the current comparative analysis focuses on criteria such as the necessity of hyperparameter optimization (HO) (i.e., Yes or No), the number of HOs and hyperparameters involved, and the computational time required to attain the final decision-making outputs. Table 1 presents the results based on the specified comparison criteria, while Fig. 12 shows the computational time required by each technique.

From the outputs detailed in Table 1, all five approaches successfully detect early damage in the box-girder bridge. However, HIC-DAD, NP-EML, and NP-IAD demonstrate lower complexity compared to GMD and

Table 1
Comparison of different unsupervised learning methods in terms of complexity.

Methods	Comparison criteria				
	False positive (%)	False negative (%)	HO	Number of HOs	Number of hyperparameters
HIC-DAD	0	0	No	0	0
NP-EML [11]	0	0	No	0	0
NP-IAD [37]	0	0	No	0	0
GDM [22]	0	0	Yes	2	4
MTUL [28]	0	0	Yes	2	3

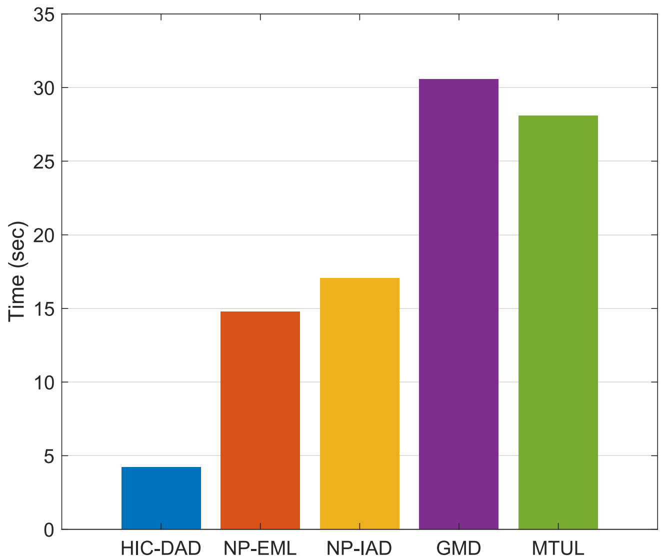

Fig. 12. Comparative analysis of computational times (in seconds) of various unsupervised learning methods applied to early damage alarming in the concrete box-girder bridge.

MTUL, as they do not require any HO or hyperparameters to obtain anomaly scores and detect damage. On the other hand, as demonstrated in Fig. 12, HIC-DAD emerges as the most time-efficient method due to requiring less time for decision-making. Despite the non-parametric nature of HIC-DAD, NP-EML, and NP-IAD, the proposed method exhibits superior performance. This conclusion is attributed to its simplified strategy for calculating anomaly scores. In contrast, NP-EML and NP-IAD rely on computing pairwise distances among all training and test instances to determine their anomaly scores, which significantly increases their computational time.

3.2. *Real short-term monitoring of a concrete cable-stayed bridge*

The current concrete cable-stayed bridge was constructed and completed in 1987 when it was the largest cable-stayed bridge in China and Asia [38,39]. This bridge consists of five spans that cover the whole dimension of 510 m, the width of 11 m, which it contains 9 m for vehicle passings and two 1 m for pedestrians. It also comprises two abutments and four piers as shown in Fig. 13. The other small spans have the same lengths of 25.15 m. The cable-stayed bridge contains two pylons with the height of 60.5 m, two cable planes, and a continuous and floatable prestressed concrete girder. During the construction of this bridge, the girder was assembled from 74 precast segments forming continuously through cast-in-place joints. The cable systems were composed of variable steel wires from 69 to 199, all of which had the diameter of 5 mm.

After the bridge repair and rehabilitation due to emerging some damage cases, a sophisticated sensing system was installed to measure structural responses as well as some environmental factors. This system consisted of more than 150 sensors installed in the bridge cables, towers, and girders [38]. The sensors were fourteen uniaxial accelerometers permanently mounted on the bridge deck, one biaxial accelerometer attached on top of one of the bridge towers, an anemometer and a thermocouple for measuring wind and temperature data, a weigh-in-motion systems for traffic, and optical fiber Bragg grating sensors for recording strain and temperature at some parts of the bridge deck and cables. During a short-term monitoring program in some days in 2008, measured acceleration responses of the bridge deck were released to use for benchmarking SHM methods [38]. Table 2 presents the details of the short-term monitoring scheme of this bridge [40,41], which are considered in this paper to validate the proposed HIC-DAD method. The vibration measurements were recorded hourly (i.e., 24 recordings for each day). The bridge status for the first eight days is undamaged, while the ninth day belongs to the damaged condition. As Li et al. [38] reported, this status was detected during an inspection in August 2008.

An OMA technique was used to extract the bridge eigenfrequencies as the main dynamic features for early damage alarming [37]. It needs to mention that the OMA was completed using data from the 13 accelerometers due to the malfunction of one of the installed accelerometers [42]. Fig. 14 depicts the identified eigenfrequencies of the cable-stayed bridge across four stable modes. The total number of eigenfrequencies corresponds to 216, with 24 frequency samples per day. The instances 1–192 represent the undamaged state of the bridge, while the instances 193–216 indicate the damaged one. A notable reduction in the bridge eigenfrequencies on the ninth day clearly demonstrates the impact of damage on the bridge stiffness and modal frequencies.

Even though it seems that the direct analysis and interpretation of the evolution of the bridge modal frequencies can detect the bridge status, this approach can be misleading due to the high variability observed in the undamaged eigenfrequencies of the bridge structure. Before the emergence of damage, significant reductions in the modal frequencies, which may be signs of the occurrence of damage, are observable in the undamaged state (i.e., the samples 1–192). Without detailed knowledge of the status of the bridge, the direct interpretation could lead to incorrect decision-making. On the other hand, the significant rate of variability observed in the undamaged state, which includes

Table 2
Short-term monitoring program of the cable-stayed bridge.

No.	Date	Bridge status	Vibration recordings
1	01 January 2008	Undamaged	24
2	17 January 2008	Undamaged	24
3	03 February 2008	Undamaged	24
4	19 March 2008	Undamaged	24
5	30 March 2008	Undamaged	24
6	19 April 2008	Undamaged	24
7	05 May 2008	Undamaged	24
8	18 May 2008	Undamaged	24
9	31 July 2008	Damaged	24

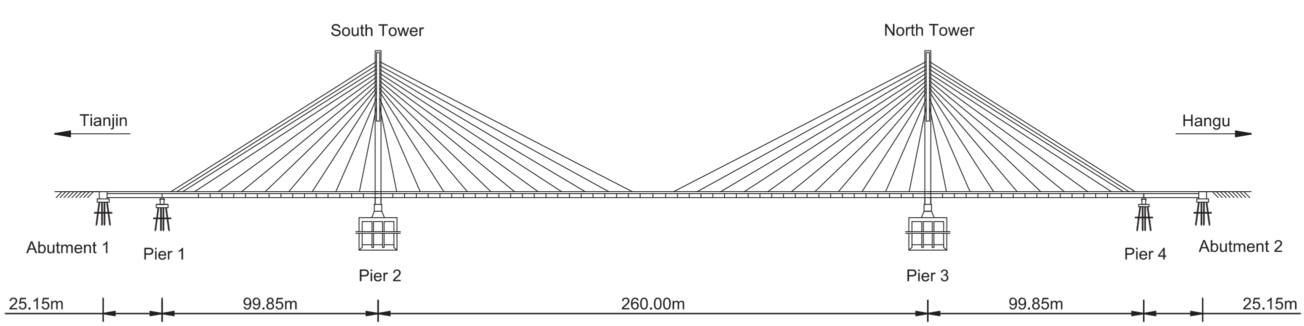

Fig. 13. The concrete cable-stayed bridge [39].

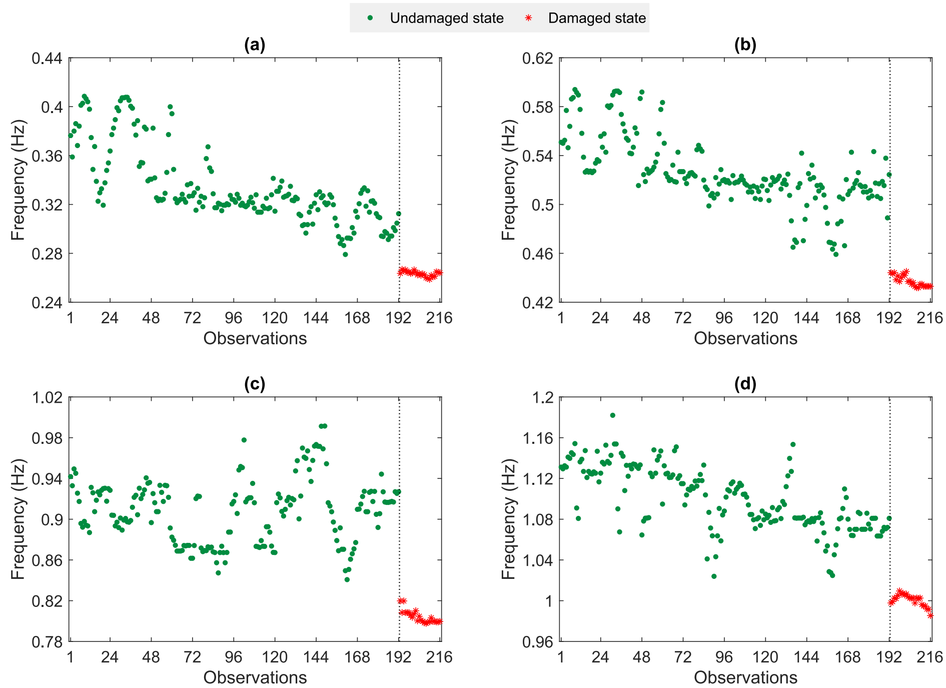

Fig. 14. Short-term eigenfrequencies of the cable-stayed bridge regarding the first-forth modes (a)-(d).

numerous upward and downward fluctuations in the modal frequencies, alongside their clear discrepancies with the damaged eigenfrequencies assist us to better demonstrate the robustness of the proposed method and its superiority over state-of-the-art techniques. Accordingly, a robust method for early damage alarming under such variable environmental conditions should be capable of: (1) considerably reducing data variability observed in the undamaged state and the training phase, and (2) distinctly discriminating between the damaged and undamaged conditions with high precision. Therefore, this rationale emphasizes the utilization of a robust and elaborate SHM method even in a restricted period of the monitoring program and obvious data changes.

To evaluate the proposed HIC-DAD method, the training data consists of 153 undamaged eigenfrequencies (n) (i.e., with the training ratio of 80 %), while the remaining undamaged modal frequencies (i.e., 20 %) are used as the validation (known test) data. These features are combined with 24 damaged eigenfrequencies (i.e., the unknown test data) to generate the test matrix containing 63 test features (m). Using the training matrix, the HIC approach partitions $\{\mathbf{x}_1,\ldots,\mathbf{x}_{153}\}$ into clusters. In this regard, Fig. 15(a) and (b) show the adjacency matrix and PMFG of the training points. Furthermore, the shortest path distances of these points used in the HIC algorithm is illustrated in Fig. 16. By generating a hierarchical binary cluster tree (i.e., a linkage) via the HIC, see Fig. 17 (a), one can automatically determine the number of clusters. As Fig. 17 (a) appears, the training features of the cable-stayed bridge should be divided into sixteen clusters. In this regard, Fig. 17(b) depicts the cluster labels of the training points. As explained in the previous example, all sixteen clusters generated by the HIC contain sufficient members, which can address the concern regarding the empty cluster problem. Moreover, the minimum number of clustered samples is identical to 5 exceeding the number of variables $p = 4$. This satisfies the requirement for reliably estimating a covariance matrix.

For early alarming of damage occurrence in the concrete cable-

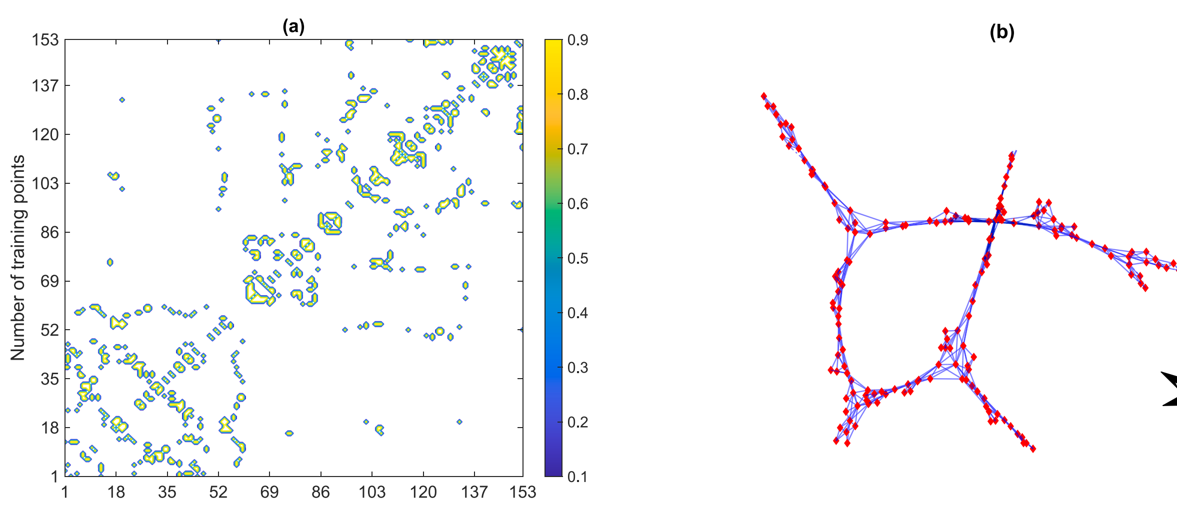

Fig. 15. The undirect graph construction based on the HIC algorithm of the concrete cable-stayed bridge indicating the adjacency matrix (a) and PMFG (b) of the training instances.

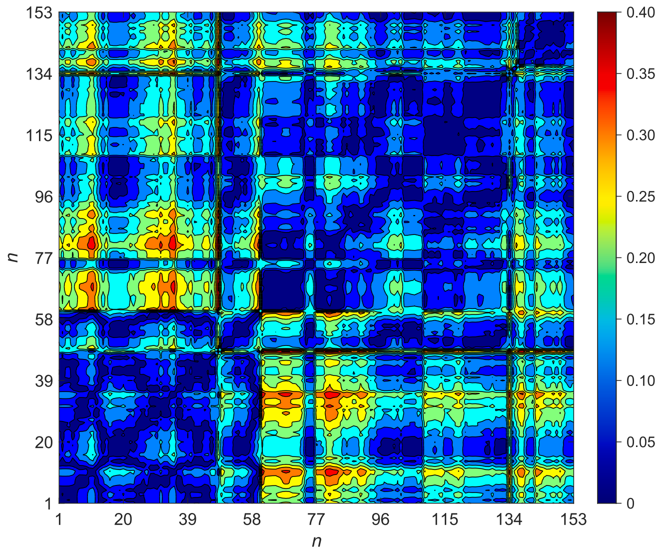

Fig. 16. The shortest distance matrix of the training points of the concrete cable-stayed bridge.

stayed bridge, the training and test features along with the clustered training points in $\{\mathbf{C}_1,\ldots,\mathbf{C}_{16}\}$ are applied to the DAD approach to determine the anomaly scores of these features. Fig. 18 illustrates the result of early damage alarming, where the dashed horizontal lines depict the SCI-determined threshold under a 1 % significance level. As can be observed, the anomaly scores of the undamaged state (i.e., regarding both the training and validation data) correctly fall below the threshold boundary without any false positive error. In this instance, it can be asserted that the proposed method mitigates environmental and operational variability, delivering consistent outputs specific to the undamaged state. Moreover, the damaged anomaly indices surpass the threshold correcting warning the occurrence of damage. A clear observation in Fig. 18 is that the quantities indicating damage are significantly beyond the thresholds. This means that the HIC-DAD can effectively distinguish between the damaged and undamaged states without relying on the threshold boundaries. Additionally, this conclusion also proves high damage detectability of the proposed method.

Similar to the previous example, the performance of the proposed method is investigated by the MSD, DAD, and GMM-MSD techniques. Fig. 19(a) shows the result of the MSD for early damage assessment of the cable-stayed bridge. It reveals that the variability patterns in the undamaged eigenfrequencies are also reflected in the MSD-determined anomaly scores. Furthermore, the magnitudes of some anomaly scores related to the bridge undamaged state are either identical to or very close to those observed in the damaged condition. Although, the direct use of the DAD approach does not reflect the same variability patterns of the modal frequencies, see Fig. 19(b), some anomaly scores of the training data manifest significant deviation from the other scores of the undamaged state. For these reasons, it can be observed in Fig. 19 that false alarm errors, which are adverse effects of environmental variability on the bridge eigenfrequencies, emerge in the undamaged state. Despite the clear distinction between the eigenfrequencies of damaged and undamaged states, i.e., suggesting that any robust anomaly detector should differentiate clearly between these conditions, it is observed that both the MSD and DAD techniques inappropriately produce anomaly scores related to the undamaged state that closely resemble, or are even identical to, those of the damaged condition. Even though the number of false alarms is relatively small, their impacts on the decision-making

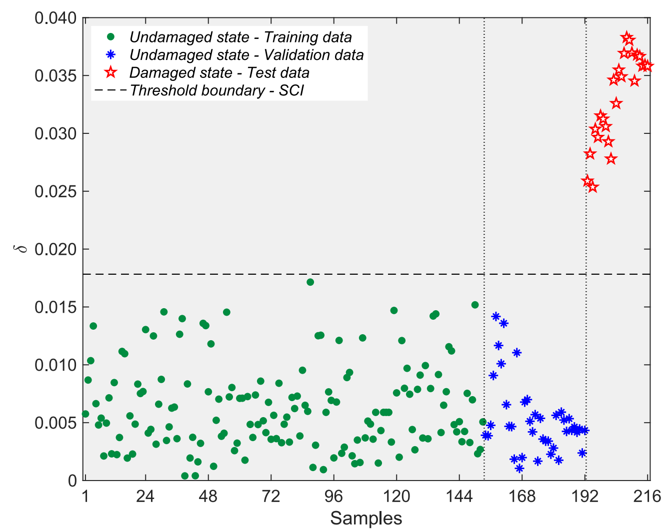

Fig. 18. Early damage alarming during the short-term monitoring program of the cable-stayed bridge by the proposed HIC-DAD method.

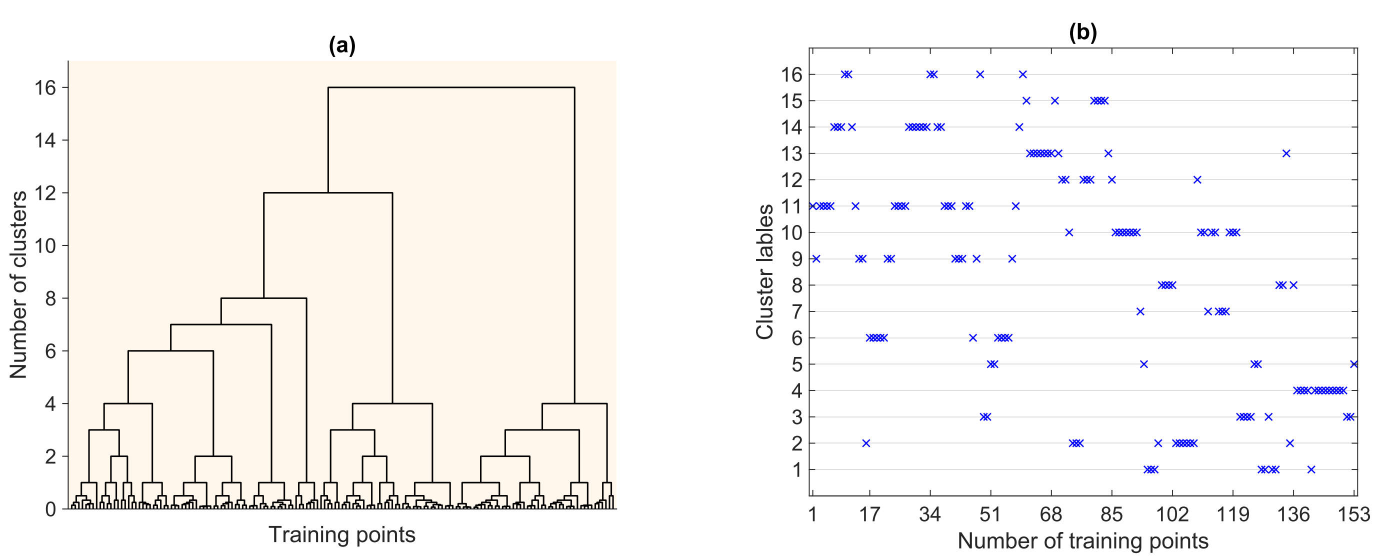

Fig. 17. More details of the HIC regarding the concrete cable-stayed bridge including the hierarchical binary cluster tree (a) and cluster labels (b) of the training instances.

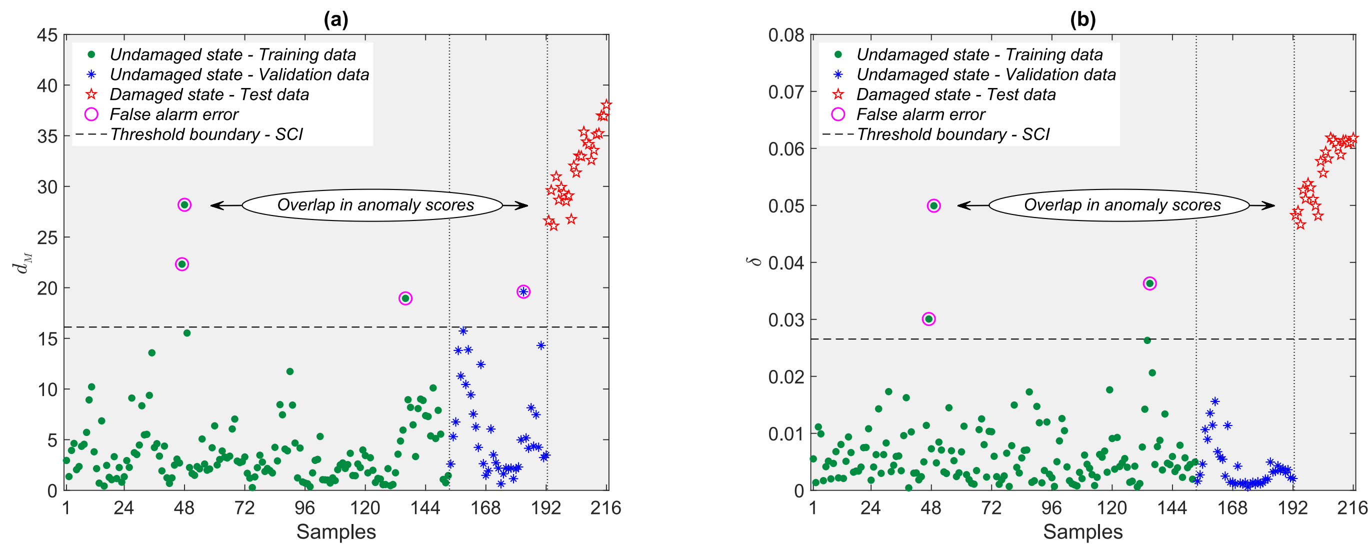

Fig. 19. Early damage alarming in the concrete cable-stayed bridge: (a) MSD, (b) DAD.

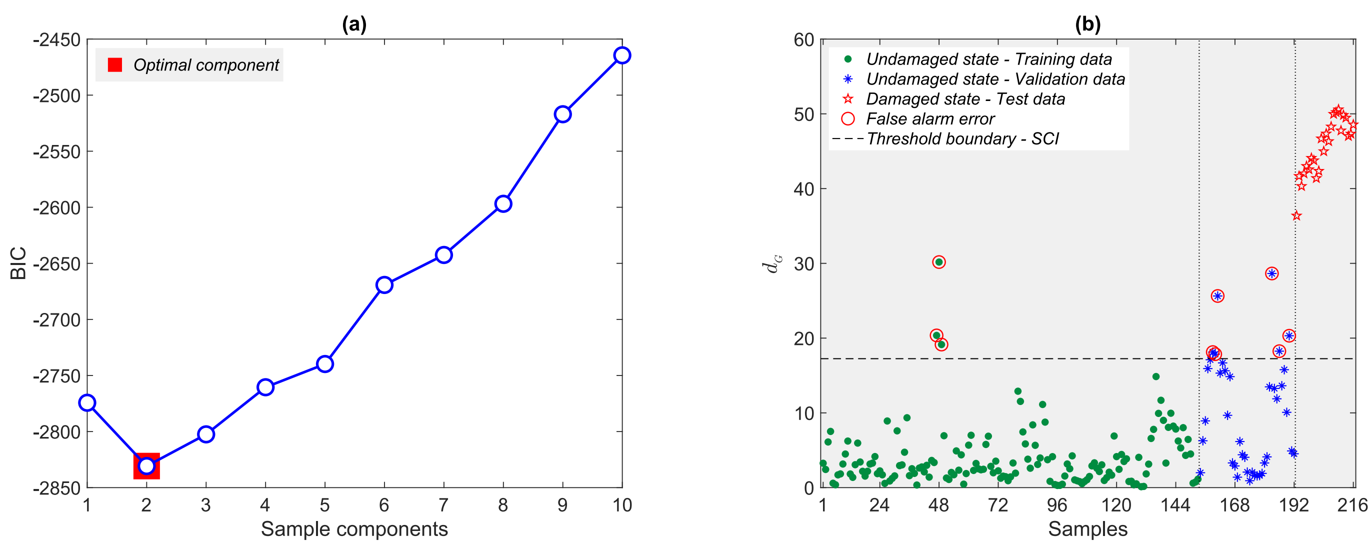

Fig. 20. Early damage alarming in the concrete cable-stayed bridge by the GMM-MSD including selection of the optimal component number using the BIC (a) and evolution of anomaly scores (b).

process are notably influential compared to the number of total samples. Given the more reliable and clearer result of early damage assessment provided by the HIC-DAD compared to the MSD and DAD, it can be concluded that the proposed method demonstrates significant superiority over its counterparts, making it particularly suitable for use in short-term SHM programs.

The result of early damage assessment via the GMM-MSD for comparing with the HIC-DAD is displayed in Fig. 20. Using 10 sample components, Fig. 20(a) shows that the BIC chooses the optimal component number, which is equal to 2. Based on the SCI for threshold estimation using the same 1 % significance level, it can be observed in Fig. 20(b) that some false alarm errors degrade the overall performance of the GMM-MSD when compared with the proposed method using the same threshold estimator. As explained, the HIC-DAD does not require any supplementary HO approach, which implies that it is not only more effective than GMM-MSD in terms of lacking false alarm and mis-detection errors but also more efficient.

Concerning the comparison of the complexity (i.e., computational time) of HIC-DAD with NP-EML, NP-IAD, GMD, and MTUL, Fig. 21 displays the computational time of all five approaches needed for obtaining anomaly scores of the cable-stayed bridge. As the number of training and test instances in both structures are roughly identical, similar results to those shown in Fig. 12 can be seen in Fig. 21. Thus, it can again be concluded that HIC-DAD is more efficient than the mentioned techniques in terms of complexity. It is also worth noting that all five techniques demonstrate similar performance with no false alarms or mis-detection errors.

4. Conclusions

In this article, a novel non-parametric unsupervised learning method (i.e., HIC-DAD) has been proposed to alarm the occurrence of early damage with limited data during short-term monitoring programs. The proposed method has contained two steps of feature partitioning via a new clustering algorithm (HIC) and unsupervised anomaly detection through a non-parametric density-based approach (DAD). The HIC algorithm could automatically divide training data into clusters without the need for additional hyperparameter optimization to select the number of clusters. To validate the effectiveness and reliability of the proposed HIC-DAD method, two real-world bridge structures with

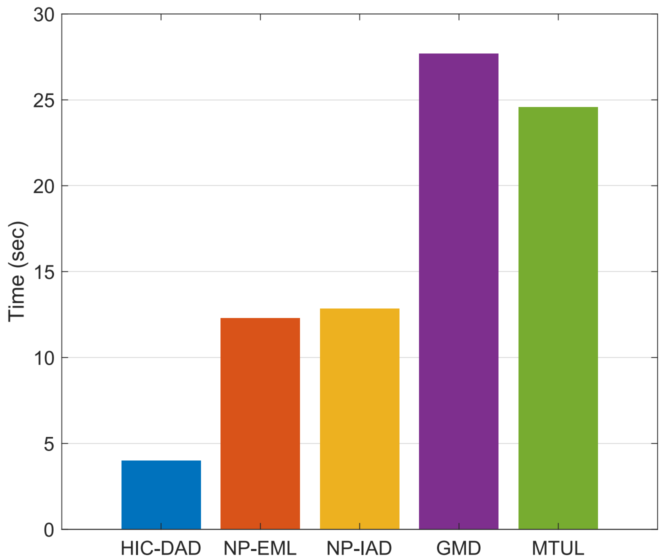

Fig. 21. Comparative analysis of computational times (in seconds) of various unsupervised learning methods applied to early damage alarming in the concrete cable-stayed bridge.

limited sets of modal frequencies from short-term monitoring programs have been considered. Several comparisons have been conducted to indicate the superiority of the proposed method against some unsupervised learning techniques.

The main conclusions of this article can be summarized as: (1) The proposed method could effectively address the challenge of environmental/operational variability and obtain accurate results of early damage alarming without false alarm (false positive) and mis-detection (false negative) errors. (2) Although it seems that environmental/operational variability is a big challenge in long-term SHM programs, it has been observed that such variability can profoundly affect the dynamic features (i.e., modal frequencies) of bridge structure in short-term monitoring schemes. 3 The success of the proposed method is significantly attributed to the proposed non-parametric clustering algorithm for partitioning of training data, which has played a vital role in mitigating the variability conditions. Without applying the process of data partitioning, the direct use of DAD could not yield reliable outputs, especially leading to false alarms using the SCI-based threshold estimator. (4) The proposed HIC-DAD method has significantly outperformed the commonly-used MSD technique in SHM applications. (5) The evaluation of HIC-DAD and GMM-MSD has revealed that the proposed method is not only more successful in mitigating the environmental change but also more efficient due to its non-parametric nature. (6) In relation to the method complexity, the comparison with some new published unsupervised learning techniques has indicated that HIC-DAD is much more efficient than the parametric approaches (i.e., GMD and MTUL). Though the other non-parametric techniques (i.e., NP-EML and NP-IAD) have been independent on any hyperparameter optimization, the proposed method has required shorter time for attaining accurate results of early damage alarming.

Despite the reliable and effective performance of the proposed HIC-DAD method for damage assessment with limited data, there are areas that could be improved in future research. The core of the proposed method relies on unsupervised learning. While this strategy is feasible for early damage assessment, incorporating advanced machine learning algorithms (i.e., semi-supervised learning, active learning, unsupervised domain adaptation, etc.) could develop more innovative solutions for anomaly detection with limited data availability. Another significant issue concerning the proposed method is related to the use of limited data of short-term monitoring programs. Although the limited features used in both structures have been reasonably influenced by environmental factors, particularly temperature, capturing all potential environmental and operational variations during a short monitoring period may be challenging. This may particularly be critical in scenarios where significant structural changes occur during extended periods, in which data is not being collected. Without data from these periods, it becomes difficult to monitor civil structures and detect abnormal conditions. To address this limitation, it is suggested to enhance the proposed method under the concepts of physics-informed machine learning, transfer learning, and machine learning-aided data generation.

CRediT authorship contribution statement

Alireza Entezami: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Hassan Sarmadi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Bahareh Behkamal:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors 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

Data will be made available on request.

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