Proceedings of International Conference on Planning, Architecture and Civil Engineering, 12 - 14 October 2023, Rajshahi University of Engineering & Technology, Rajshahi, Bangladesh

Paper ID: CE 0152

A Statistical Pattern Recognition for Structural Health Monitoring Using Vibration Signals

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Abstract

Structural health monitoring (SHM) is crucial to detect damage in structures at an early stage, allowing timely maintenance and repair to ensure their safety and longevity. This paper presents a study that investigates the feasibility of using a statistical pattern recognition-based method for SHM using a laboratory structure. The proposed approach relies solely on signal analysis of the measured vibration data, making it cost-effective and attractive for the development of an automated health monitoring system. Unlike traditional SHM methods, the proposed approach does not require labor-intensive tuning, expert knowledge, or extensive training, reducing the time and cost required for SHM. The large-scale laboratory structure at Qatar University provides a unique platform to obtain a large dataset of vibration signals under several structural damage scenarios. The study presents a technique to identify damage using Mahalanobis distance between vibration signals of damaged and undamaged conditions. The proposed approach has the potential to be a practical and efficient solution for SHM in civil, mechanical, and aerospace engineering applications, contributing to the development of reliable and accurate health monitoring systems for structures.

Keywords: *Structural health monitoring; Statistical pattern recognition; Vibration analysis; Mahalanobis distance; Automated monitoring systems.*

1 Introduction

The construction of structures involves significant effort and aims to achieve long lifespans, necessitating the implementation of proper measures to control and assess their state of conservation. Over time, structures undergo continuous deterioration due to operational and environmental conditions, manifesting in various forms such as corrosion, fatigue cracks, erosion, and strength reduction (Animah et al., 2018). Consequently, it is crucial to investigate and analyze these degradation processes to determine the current state of conservation. Whether modern or considered ancient, structures' capacities diminish with daily usage, external factors, and the passage of time, ultimately posing risks of collapse, as observed in cases like the San Marco bell tower in Venice or the civic tower of Pavia (Binda et al., 1992).

Assessing the structural health of buildings can be performed periodically or continuously. Regardless of the approach, initial data collection serves as a vital step for interpretation and subsequent analysis to determine the need for intervention and identify suitable intervention strategies. This process falls within the domain of Structural Health Monitoring (SHM), which involves implementing a damage detection strategy by measuring the structural response of specific key parameters under operational or environmental conditions (Farrar et al., 2013; Sohn et al., 2004). SHM systems encompass various components, including measurement systems, acquisition systems, data processing systems, communication/warning systems, identification/modeling systems, and decision-making systems (Ceravolo et al., 2016). Long-term continuous measurements of key parameters in the structural response provide valuable insights into the overall health and anticipated performance of the structure. Numerous researchers have explored diverse approaches to structural health monitoring. Modal analysis of acquired signals has been widely employed (Li et al., 2021; Barbosh et al., 2020), although it may yield false results due to noise interference in lower modes and the potential non-excitation of higher modes. FRF analysis has also been utilized (Cherid et al., 2022), but it is subject to limitations such as linearity assumptions, sensitivity to environmental conditions, limited spatial resolution for localized damage, dependence on excitation signals, susceptibility to measurement noise and errors, and challenges in distinguishing closely spaced or overlapping modes. Artificial neural networks (ANN) have been leveraged for damage detection (Avci et al., 2017), but they require high-level computational resources and rely on data from damaged conditions for supervised learning, which may not be readily available in most cases.This paper introduces a novel damage detection system utilizing unsupervised learning. The system collects vibration data from both damaged and undamaged structures and employs statistical tools to identify outliers in the acceleration response, facilitating damage detection (Figure 1). The advantage of this method lies in its efficiency, as it does not necessitate extensive computations or time consuming analysis. It operates directly on the acquired data, eliminating the need for modal analysis or decomposition, thereby enhancing convenience and practicality.

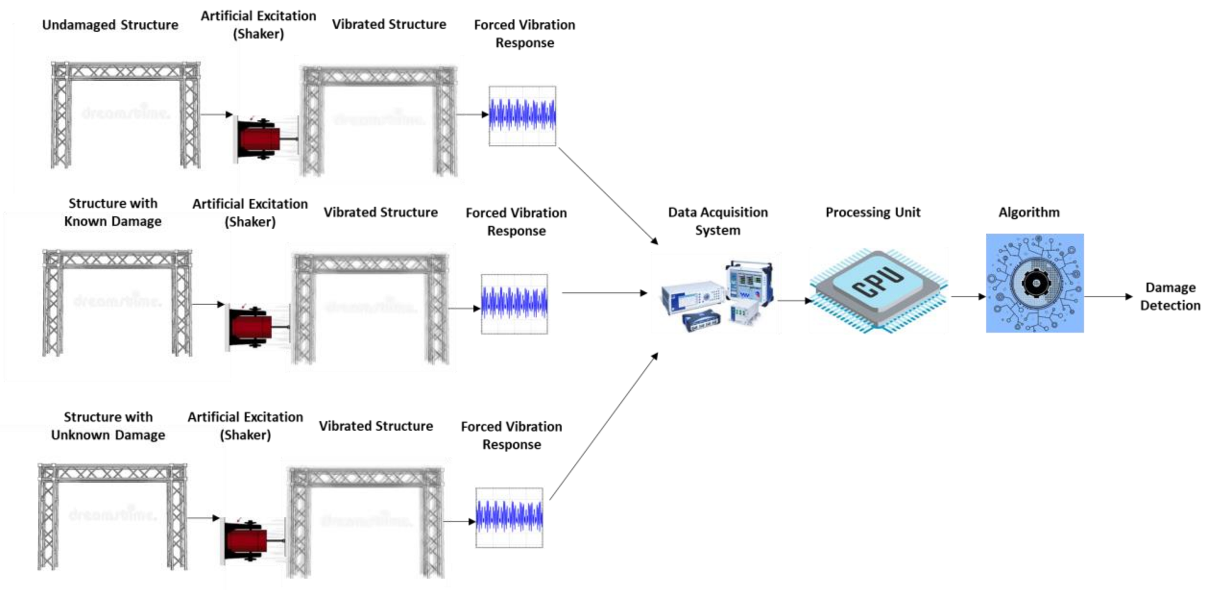

Figure 1. Unsupervised Learning

2 Theoretical Background

This paper introduces a novel approach that utilizes Mahalanobis Distance (MD) for damage detection in practical applications. Unlike other methods, this approach directly applies MD to the vibration response, specifically acceleration.

Mahalanobis Distance is a highly effective multivariate distance metric that quantifies the distance between a point (vector) and a distribution. The methodology involves several key steps:

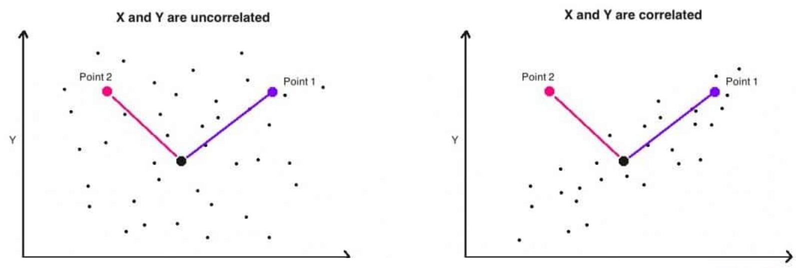

Figure 2. Mahalanobis Distance (Retrieved from https://www.mach inelearningplus.com/statistics/mahalanobis-distance)

- The columns of the data are transformed into uncorrelated variables.
- The columns are then scaled to ensure equal variance across all variables.
- Finally, the Euclidean distance is calculated using the transformed and scaled data

$$D^2 = (x-m)^T.C^{-1}.(x-m) \tag{1}$$

When comparing two similar rows of data, the mean of the MD will be close to one. As the data deviates further from the standard, the MD value will deviate from one. By calculating the difference from one, it becomes easier to identify the data points that deviate significantly from the standard, indicating potential damage.

3 Experimental Studies

In accordance with reference (Avci et al., 2018), the subsequent sections will delve into a comprehensive examination of the methodology's effectiveness in distinguishing various structural configurations. This evaluation is based on the analysis of experimental data acquired from a prominent grandstand simulator located at Qatar University (QU). The upcoming sections will provide extensive details regarding the test structures, conducted experiments, and the outcomes obtained.

3.1 Test Structure

Ongoing analytical and experimental studies at Qatar University are dedicated to the field of Structural Health Monitoring (SHM) and vibration serviceability of stadiums. The main objective of these studies is to develop effective techniques for detecting structural damage in modern stadiums. To ensure the reliability and accuracy of these newly developed techniques, it is crucial to validate them through experimental testing in a controlled laboratory environment.

To facilitate the experimental testing, Qatar University (QU) has constructed a large grandstand simulator. This test structure primarily comprises a hot-rolled steel frame, which has been designed and constructed in accordance with modern grandstand specifications. The steel frame, illustrated in Figure 3, has a footprint dimension of 4.2m × 4.2m and can accommodate up to 30 spectators. Safety considerations have been meticulously integrated into the structural design.

The steel frame consists of 8 girders, 25 filler beams, and 4 columns. The girders have a length of 4.6m, while the cantilevered portion comprises 5 filler beams measuring approximately 1m, and the remaining 20 beams are 77cm each. The two longer columns have a length of around 1.65m.

It is important to note that for the purpose of this specific study, nonstructural elements such as risers, treads, seats, and handrails have not been installed in the grandstand simulator. The focus of the study is to collect vibration data using the steel frame structure alone, under various scenarios representing different types of structural damage.

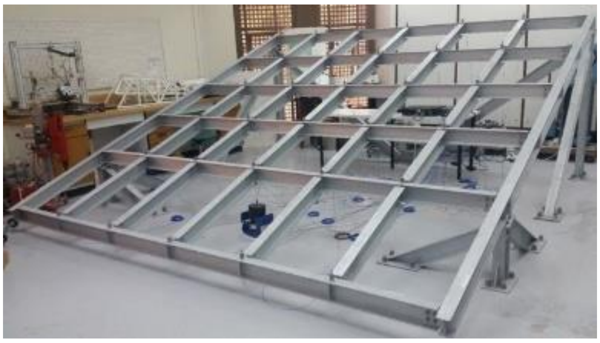

Figure 3: Qatar University Grandstand Simulator (QUGS) (Avci et al., 2018)

3.2 Instrumentation

In order to monitor the structural response, a total of 30 accelerometers were strategically installed at the joints of the steel frame. Among these, 3 B and K 8344 accelerometers were used in conjunction with 27 PCB 393B04 accelerometers. Magnetic mounting plates were utilized to securely attach the accelerometers to the designated positions, as depicted in Figure 4.

To induce vibrations in the structure, a modal shaker (Model 2100E11) was employed, as illustrated in Figure 5. The shaker received the input signal through a SmartAmp 2100E21-400 power amplifier, as shown in Figure 6. The shaker was responsible for generating controlled vibrations within the structure.

For the purpose of data acquisition, two separate data acquisition devices were utilized. One device was dedicated to generating the input signal for the shaker, while the other device was responsible for collecting the output data from the accelerometers. These devices facilitated the acquisition of accurate and comprehensive data throughout the experimental testing process.

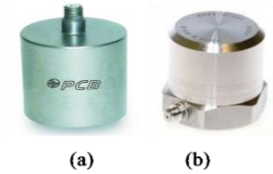

Figure 4: The accelerometers.
(a) PCB 393B04. (b) B&K 8344.

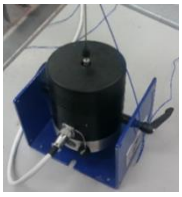

Figure 5: The modal shaker (TMS 2100E11).

Figure 6: Data acquisition setup

3.3 Damage Scenarios

During the experimental setup, the simulation of structural damage involved deliberately loosening the bolts at the connections between the beams and girders, as illustrated in Figure 7. A total of 31 structural scenarios were created to simulate different types of damage in the experiment.

The initial scenario, Scenario 1, served as the reference case where no damage was present (undamaged condition). Subsequently, in Scenarios 2 to 31, damage was systematically introduced to each joint, beginning with Joint 1 and progressing up to Joint 30. The corresponding joint numbers for each scenario are clearly indicated in Figure 8.

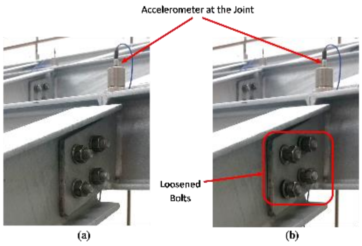

Figure 7: Structural damage introduced to a joint by loosening its bolts.

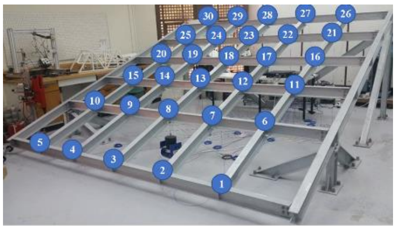

Figure 8: Location of the damaged joint for scenarios 1 to 31

3.4 Damage Identification

This paper entails the collection of acceleration responses from an intact structure, which serves as the reference. Subsequently, the acceleration responses from various structural conditions are measured, and the Mahalanobis Distance (MD) of each response is calculated in relation to the reference. The mean MD is then computed, whereby for the undamaged condition, characterized by minimal deviation from the reference, the mean MD value approaches one. Conversely, for damaged conditions, the mean MD values deviate significantly from one. DI can be calculated using equation 2. By plotting the deviations of DI for different scenarios, the presence of damage can be easily identified.

$$DI = |\text{Mean MD} - 1| \quad (2)$$

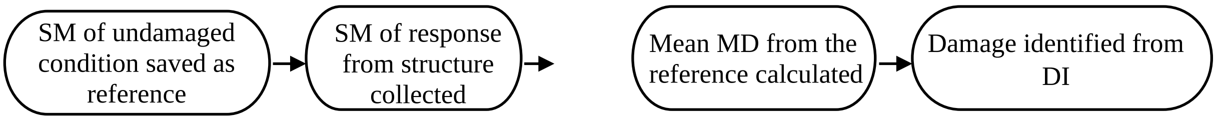

Figure 9: Flow chart for Damage Detection

In order to demonstrate the efficacy of this method, various damage cases will be presented wherein damage is deliberately introduced at different nodes of the structure. Additionally, sensors will be strategically positioned at different nodes to capture the structural response. By examining the obtained data from these different damage cases and sensor locations, the effectiveness and reliability of the proposed method can be thoroughly evaluated. Table 1 shows different damage cases and Table 2 shows different sensor positions considered in this paper.

Table 1. Damage Cases.

Case	Damaged Node	Remarks
Case 1	Node 18	Damage at middle of the structure
Case 2	Node 6	Damage near support
Case 3	Node 1	Damage at cantilever portion

Table 2. Sensor Positions.

Position	Sensor Position	Remarks
Position A	Node 13	Sensor at middle of the structure
Position B	Node 21	Sensor near support
Position C	Node 3	Sensor at cantilever portion

3.4.1 Damage Identification for Positon A

To detect structural damage, the acceleration responses from node 13 will be collected for different damage cases 1-3. By carefully analyzing the variations and patterns within these responses, it becomes possible to identify the presence of structural damage. This process is visually depicted in Figure 10, where the changes in the acceleration responses are analyzed in terms of proposed DI to detect the structural damage.

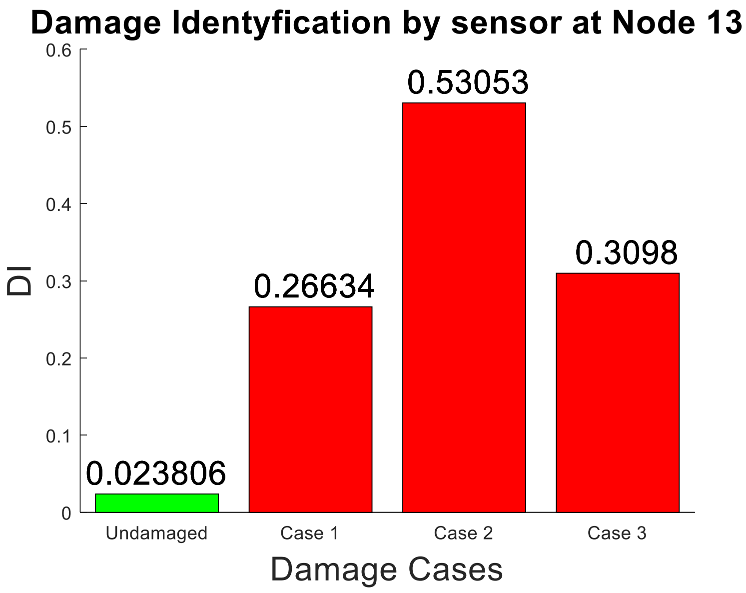

Figure 10: Damage Identification by sensing at Position A

3.4.2 Damage Identification for Positon B and C

In addition to node 13, the acceleration responses from nodes 3 and 21 are also analyzed to detect structural damage. By examining the changes in these responses, the presence of damage can be detected. This comprehensive analysis at multiple sensor locations enhances the effectiveness of the proposed method in detecting structural damage.
The findings from these analyses are presented in Figure 11 and Figure 12, highlighting the capability of the method across different nodes.

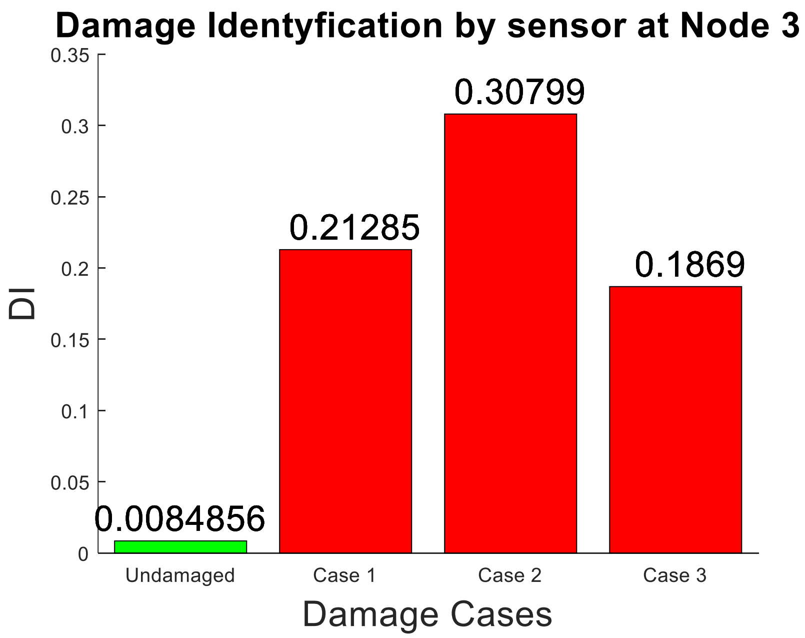

Figure 11: Damage Identification by sensing at Position B

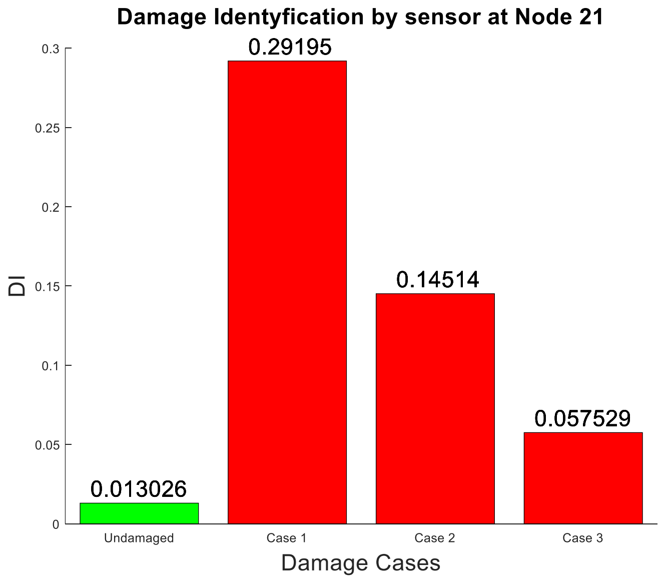

Figure 12: Damage Identification by sensing at Position C

4 Conclusions

At various sensor points (nodes) across the structure, the suggested method for damage identification utilising vibration signals was assessed. To find structural deterioration, acceleration responses from nodes 13, 3, and 21 were examined.

Different types of damage were successfully identified as structural damage by examining the differences and patterns in the acceleration responses from node 13 (position A). The proposed DI amply demonstrated the existence of harm, verifying the viability of the suggested approach.

Additionally, the acceleration responses from nodes 3 and 21 (positions B and C) were also examined to detect structural damage. The analysis revealed noticeable variations in terms of DI, further confirming the ability of the method to identify damage at different sensor positions. Based on these findings, further study can be done to identify the location of structural damage by examining the variations and patterns in the acceleration responses at different sensor positions.

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