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Wavelet-Based Damage Sensitive Features Extraction for Structural Health Monitoring of Bridges

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ABSTRACT

Structural Health Monitoring (SHM) of bridges is fundamental to ensure public safety and extend the life of infrastructures. Early detection of structural damage, through the extraction of Damage Sensitive Features (DSFs), plays a key role in improving maintenance strategies and reduce the risk of structural failure. This study proposes a data-driven methodology for identifying and extracting wavelet-based DSFs, which captures critical information about the structural integrity of bridges. Starting from data recorded by the sensor networks installed on the bridge, the approach employs time-frequency analysis techniques to process and analyze large datasets, thereby enabling the extraction of features highly sensitive to damage. By leveraging wavelet decomposition, this method not only isolates features indicative of damage but also identifies the specific frequency bands where damage has the most substantial impact. A modal analysis-driven selection of wavelet decomposition levels further ensures that the analysis focuses on the most relevant frequency scales for detecting structural changes, enhancing the sensitivity and accuracy of DSF extraction. The methodology is validated using real-world data to assess the ability of the extracted DSFs to discriminate between healthy and damaged states of the bridge. Results demonstrate that the proposed approach effectively identifies early indicators of structural damage, providing valuable insights into the bridge's condition. The use of a data-driven algorithm is particularly advantageous due to its versatility and generalizability, as it is not limited to specific types of structures or conditions. This makes the approach suitable for automating the management of bridge monitoring and maintenance. Therefore, the findings suggest that time-frequency-based DSF extraction is a reliable tool for SHM systems, with significant implications for the future of bridge safety, maintenance, and infrastructure management.

Keywords: Structural Health Monitoring, Damage Sensitive Features, Wavelet Transform, Data Driven

Bridge Monitoring.

1. INTRODUCTION

The field of Structural Health Monitoring (SHM) has emerged as an important area of research dedicated to assess the condition of bridges throughout their life, particularly in response to the increasing number of bridge-related accidents in recent years [1]. Within SHM, damage is defined as any alteration in a structure that may compromise its performance. It is important to note that such changes do not necessarily lead to immediate failures; rather, they often represent a gradual deterioration that, if left undetected, could compromise the structure's functionality [2]. Therefore, early detection of damage is fundamental to prevent such outcomes and ensure the ongoing safety and reliability of structural systems [2, 3]. Among the various SHM strategies, vibration-based approaches have gained significant attention [4, 5] as they leverage the dynamic response of the structure to identify potential damage, offering an efficient way to monitor the status of complex systems [6]. One particularly effective framework within vibration-based monitoring is statistical pattern recognition, which involves analyzing the statistical distribution of specific parameters known as Damage Sensitive Features (DSFs). By comparing the distributions of parameters extracted from an unknown structural condition to those of a healthy reference state, changes in the system's properties can be identified, thereby indicating potential damage [2]. To be effective in damage assessment, DSFs should be representative of the structural properties while remaining insensitive to external influences, such as environmental and operational variations, which may alter the dynamic response without necessarily indicating damage [7]. Various techniques have been employed in vibration-based SHM to extract reliable DSFs. These techniques operate in the modal domain [8], time domain [4, 7], and quefrequency domain [6]. However, the time-frequency domain, thanks to the Wavelet Transform (WT), has proven to be a powerful tool for damage detection, even in cases of low-severity damage. Its ability to handle transient, nonstationary, and nonlinear signals allows for the identification of subtle structural alterations that might otherwise go undetected [1, 5, 9]. WT has been successfully applied both for modal identification and for direct damage detection. In particular, its effectiveness has been demonstrated in numerical models [1, 5], laboratory test cases, and real-world implementations [5]. For instance, Kankanamge et al., in [5], proposed using the number of ridges in the WT scalogram as a damage signature, though this approach requires significant user expertise and manual intervention. Additionally, Fallahian et al., in [10], combined WT with principal component analysis to develop a system based on a combination of sparse coding and deep neural network for damage assessment.

In this study, a novel data-driven DSF extraction technique based on the Discrete Wavelet Transform (DWT) is proposed for structural damage detection. The motivation behind this method is its applicability in real-world monitoring processes, necessitating a fully automated and computationally efficient approach with minimal facilities requirements. To achieve this, the proposed methodology is fully data-driven, so it does not require any model of the monitored bridge, and it utilizes a sparse sensor network on the structure, followed by a sensor fusion phase and DWT analysis, thereby reducing computational costs, both because the number of signals to be analyzed is reduced to a single signal per acquisition and because no model is required. The mean frequency of the DWT coefficients is extracted as a feature to compare the current state of the structure with a reference condition. The proposed method has been validated on a real-world testbed: the Old Ada Bridge. In this case study, the Kullback-Leibler (KL) divergence has been employed to compare the distributions of mean frequencies across different damage scenarios. The results demonstrate that the method is capable to detect structural damage even in cases where alterations in modal parameters are minimal and approximately undetectable in a traditional approach.

The remainder of this paper is structured as follows: Section 2. provides a theoretical background of the DWT. Section 3. introduces the Old Ada Bridge case study, detailing the monitored structure and the experimental setup. Section 4.1. presents the proposed damage detection technique, describes its implementation, and discusses the obtained results. Finally, conclusions are outlined in Section 5..

2. THEORETICAL BACKGROUND: DISCRETE WAVELET TRANSFORM

The Discrete Wavelet Transform is a time-frequency signal processing technique used to analyze signals and images in a multi-resolution approach, thanks to which trends, instantaneous changes, and discontinuities can be identified in a signal [1, 9]. DWT extracts coefficients $C_{j,k}$ from a discrete signal $x(n)$ according to the relation in Eq.(1), where a decomposition over the translated and dilated mother wavelet $\psi(n)$ is performed [5]:

$$C_{j,k} = 2^{-\frac{j}{2}} \sum_{n} x(n)\ \psi(2^{-j}n - k) = 2^{-\frac{j}{2}} \sum_{n} x(n)\ \psi_{j,k}(n) \tag{1}$$

where $\psi_{j,k}(n)$ are the DWT basis functions obtained by scaling and shifting the mother wavelet $\psi(n)$, according to the scaling parameter j, which controls the frequency resolution, and to the translation one k, related to time localization [5, 9]. In practical application, the DWT is implemented using a two-stage filter to the signal: a low-pass filter that isolates the approximation coefficient and a high-pass one whose output is the so-called detail coefficient [11]. Both the outputs of the two-stage filter contains half of the frequency content of the original signal. On the approximation coefficient, the same two-stage filter can be re-applied N_L times to split the signal into several bandwidths further. N_L is denoted as the number of levels of the DWT, given by Eq.(2), where N_s is the number of samples [11].

$$N_L = \Big\lfloor \log_2(N_s) \Big\rfloor \tag{2}$$

3. OLD ADA BRIDGE DESCRIPTION

The Old Ada bridge, built in 1959 in Japan as a simply supported steel truss bridge , as shown in Figure 1, was demolished after being replaced by a new bridge in 2012 [12]. The main span of the bridge has a length of $59.2m$, and its width was $3.6m$, while the maximum height of the bridge was $8.2m$ [13]. Before its demolition, the online dataset [14] was created to provide researchers with real data for SHM [13].
The main focus of the dataset was the damage assessment under vehicle load excitation. Therefore, during the acquisition time, the test vehicle, whose weight was approximately $21kN$, crossed the bridge at a constant speed, while other traffic was not allowed on the bridge. To control the average speed of the car, three optical sensors were mounted on the bridge: two at the ends and one at the mid-span to track the instant of time at which the test vehicle was at these points. In addition, to record the response of the bridge under vehicular load, eight uniaxial accelerometers were installed on the bridge, as shown in Figure 1, along the vertical direction (the Z in Figure 1) [12, 13].
During the experimental activity, five different damage scenarios were realized on the bridge, as detailed in Table 1, where the variation in the first natural frequency (Δf_1) of the bridge caused by them is also reported [12]. In them, the speed of the test vehicle was 40 km/h; therefore, in Table 1, the corresponding undamaged condition is considered. These scenarios were realized to reproduce damages similar to those found on the bridge during previous inspections, probably due to corrosion or overloading [12].

4. THE PROPOSED TECHNIQUE FOR DAMAGE DETECTION

4.1. Description of the technique

The proposed data-driven technique for damage detection is based on a multi-step analysis to evaluate structural conditions using signals acquired from a network of sensors and it is summarized in Figure 2. The first step involves normalizing the acquired signals to have zero mean and unit standard deviation, ensuring data comparability regardless of operating conditions and individual sensor characteristics. Next,

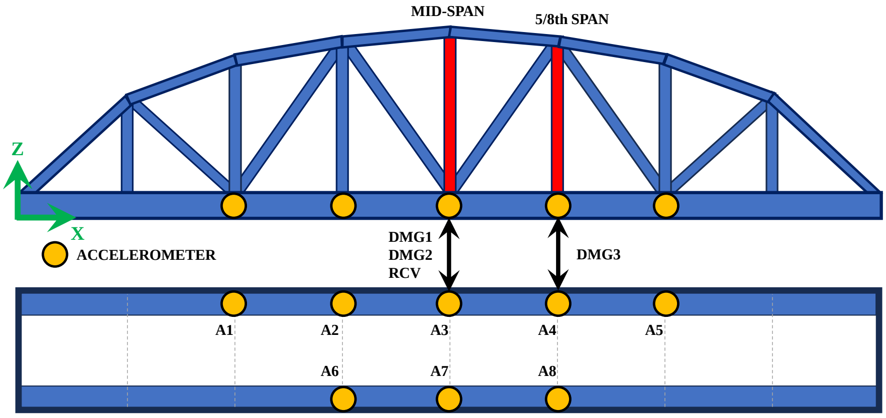


Figure 1: Old Ada Bridge: sensors and damages positions

Table 1: Overview of the damage scenarios, including the corresponding number of acquisitions and the variation in the first natural frequency for each of them

Scenario	Description	Location	Intensity	No. Acquisitions	Δf_1 [%]
INT	Undamaged bridge	-	-	10	-
DMG1	Cut of one vertical truss	Mid-span	50%	12	+0.03
DMG2	Cut of one vertical truss	Mid-span	100%	10	-3.22
RCV	Recovery of the cut truss	-	-	10	-
DMG3	Cut of one vertical truss	5/8th span	100%	10	-1.58

the mean of all the signals recorded by sensors during a test is computed, allowing sensor fusion, reducing the total number of signals that need to be processed, thereby reducing computational complexity. The obtained signal is then processed using the DWT, which enables the analysis of frequency content at multiple time scales, as in Section 2.. In particular, it is preferred to the continuous wavelet transform because it is less computationally expensive and because it is not redundant [1, 5], making the proposed method more applicable in real-world monitoring processes. From the spectrum of the discrete wavelet coefficients, the mean frequency is extracted and used as the DSF. This is because structural damage typically alters the dynamic properties of the system, leading to shifts in the frequency content of its response. A significant alteration in the DSF may indicate structural changes, enabling the detection of potential anomalies or damage. Therefore, the variation in the extracted mean frequency is quantified by comparing the reference case with the case under analysis.

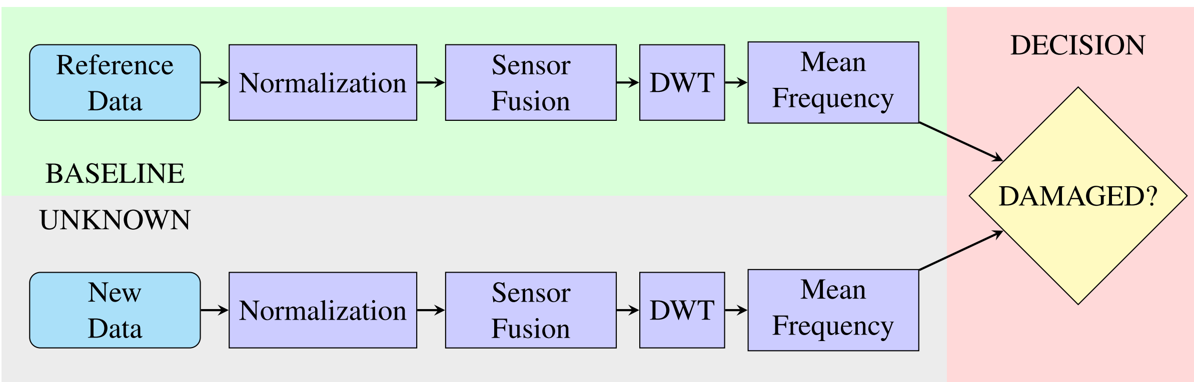
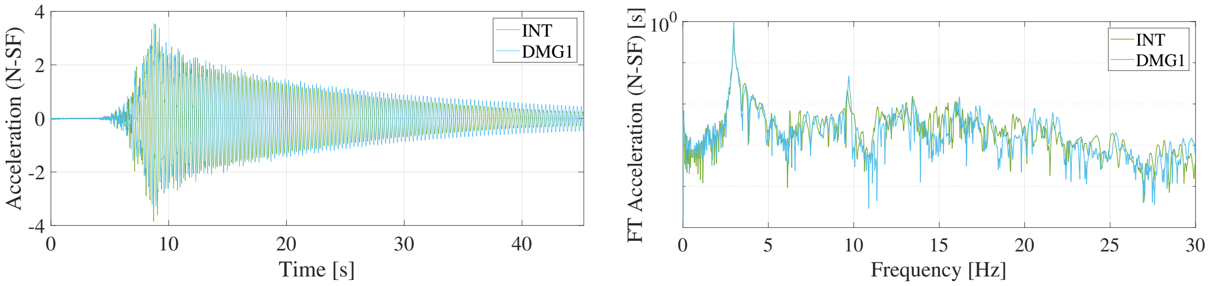


Figure 2: Workflow of the proposed technique

4.2. Results and discussion

The application of the proposed damage detection technique, described in Section 4.1. begins with the normalization and sensor fusion steps. The time-history output and its Fourier Transform (FT) from the sensor fusion phase is shown in Figure 3, for both the undamaged and damaged cases. Specifically, Figure 3 refers to the DMG1 scenario, which represents the least intense damage condition and is, therefore, the most challenging to identify using traditional modal analysis [12], as shown by the barely perceptible differences between the two signals both in time and frequency domain in Figure 3.



(a) Time-history **(b)** Magnitude of the FT

Figure 3: Output signal of the normalization (N) and sensor fusion (SF) phase for both the undamaged (green) and damage DMG1 (cyan) cases

Subsequently, the DWT of the obtained time-history is performed, choosing a *dmey* mother wavelet. In the case of the Old Ada bridge, the sampling frequency was set to $f_s = 200Hz$ [13], with a total number of samples is $N_s = 9050$. This results in a DWT decomposition level of $N_L = 10$, according to the rule in Section 2.. Therefore, the corresponding bandwidths $\left[f_{min}, f_{max}\right]$ for each level are provided in Table 2, which also indicates the number of modes (N_M) that fall within each of the identified ranges [12].

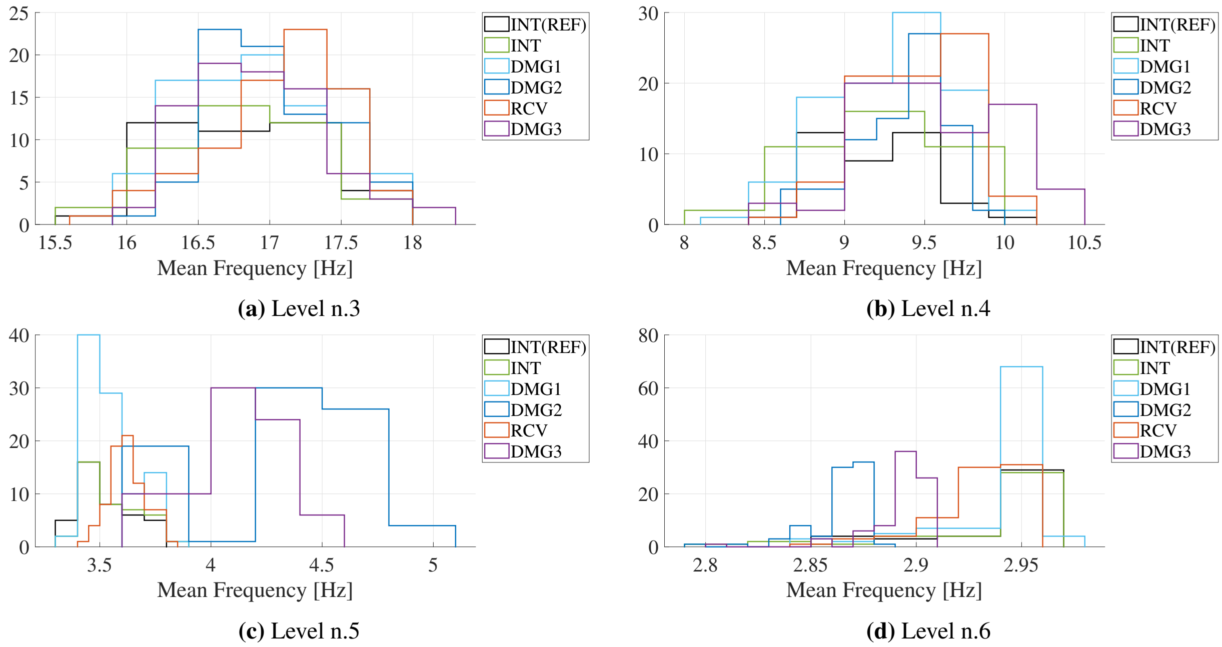
Table 2: Bandwidths determined by the DWT decomposition and the corresponding number of modes falling within each identified range

LVL	1	2	3	4	5	6	7	8	9	10
$\mathbf{f_{min}}[Hz]$	50	25	12.50	6.25	3.13	1.56	0.78	0.39	0.20	0
$\mathbf{f_{max}}[Hz]$	100	50	25	12.50	6.25	3.13	1.56	0.78	0.39	0.20
$\mathbf{N_M}$	0	0	1	3	0	1	0	0	0	0

To assess the effectiveness of the proposed technique in damage detection, the variation in the distribution of the mean frequency of the DWT coefficients across different decomposition levels is analyzed. This variation is quantified using the Kullback-Leibler divergence, as defined in Eq.(3), where $R(j)$ and $S(j)$ are the probability distributions of the mean frequencies in the reference and under-investigation conditions, respectively [15].

$$D_{KL}(R||S) = \sum_j R(j) \log\left(\frac{R(j)}{S(j)}\right) \tag{3}$$

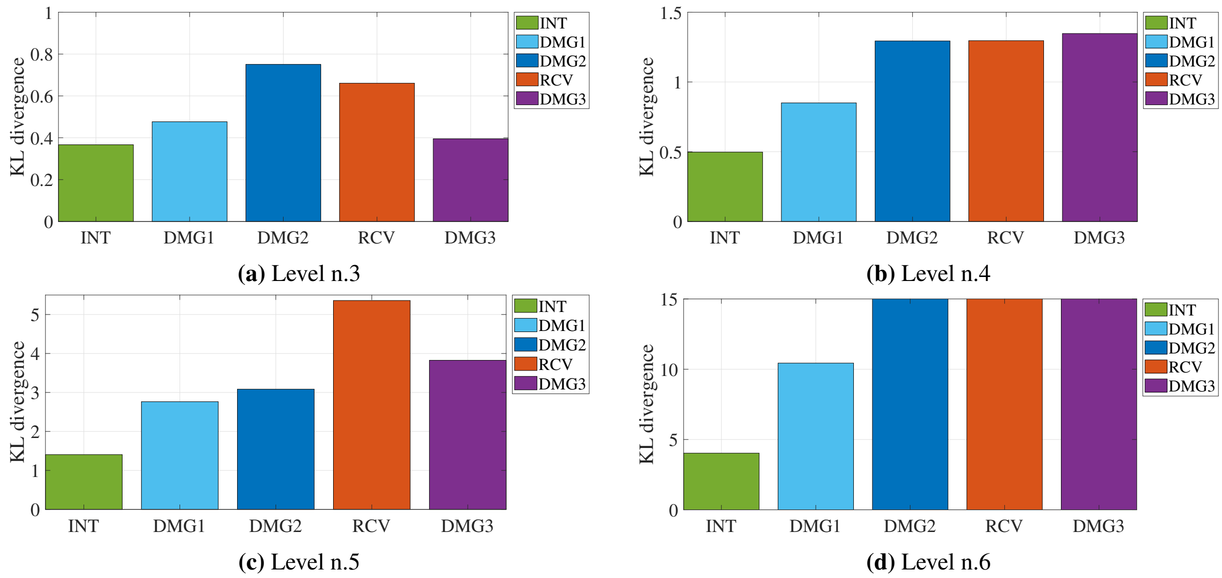
The KL divergence was chosen because it is sensitive to changes in shape and concentration, and it accounts for the full probabilistic structure of the data.
For this analysis, the reference distribution is defined as the level-by-level distribution of mean frequencies obtained from the DWT coefficients computed from the first five acquisitions of the undamaged case (called INT(REF)). The distributions of mean frequencies are then evaluated for both the remaining acquisitions of the undamaged case and those corresponding to damage scenarios, as shown in Figure 4, according to Table 1. In order to select the levels (and consequently the frequency bandwidths) in which the variation is evaluated, it is essential to possess prior knowledge of the modal behavior of the structure. Indeed, the focus is on the levels that contain the vibration modes, where the effect of loading effects is not relevant since these levels correspond to the bridge's resonance frequencies, and no significant



(a) Level n.3 (b) Level n.4 (c) Level n.5 (d) Level n.6

Figure 4: Mean Frequency distributions in all the available damage scenarios in Table 1

variations in environmental conditions are present in the Old Ada dataset [13].
As shown in Figure 5, at all levels that contain the vibration modes of the bridge, the KL divergence between the distributions of the mean frequencies extracted from the spectra of the DWT coefficients effectively tracks all the damage scenarios.



(a) Level n.3 (b) Level n.4 (c) Level n.5 (d) Level n.6

Figure 5: KL divergence between the Mean Frequency distributions in all the available damage scenarios in Table 1 for the DWT decompositions levels from n.3 to n.6 as in Table 2

Notably, the method is also able to detect damage at level n.5, despite the fact that, according to Table 2, this level does not contain any vibration modes of the bridge. This can be explained by its proximity to mode n.1 ($f_1 = 2.98Hz$) and mode n.2 ($f_2 = 6.88Hz$) [12], which means that, although it does not directly encompass a modal frequency, it is still influenced by the dynamic behavior of these nearby modes. As a result, damage affecting modes n.1 and n.2 induces variations in the frequency components present at level n.5, allowing the KL divergence to detect structural changes even in this range. This highlights the method's sensitivity to low frequency shifts, which are often indicative of structural deterioration.

Additionally, across all the ”modal” levels, the KL divergence for the RCV damage case remains higher than that of the undamaged condition. This observation suggests that, despite the recovery of the cut truss element at mid-span, the structural state is not completely identical to that of the undamaged case. One possible explanation is that the repair may have introduced residual stresses, slight geometric imperfections, or variations in stiffness that differentiate the restored structure from its original condition. These factors, although potentially subtle, can still influence the frequency content of the response, leading to detectable differences in the statistical distributions analyzed by the KL divergence. This underscores the method’s capability to distinguish even minor structural modifications.

5. CONCLUSIONS

This study presents a novel method to extract DSFs based on the DWT for structural damage detection. The approach exploits the capability of the wavelet transform to capture both subtle and abrupt changes in signals, enabling an effective assessment of structural integrity. By extracting the mean frequency of the DWT coefficients and analyzing its statistical distribution, the proposed method successfully identifies damage scenarios in the real-world case study of the Old Ada Bridge. Compared to traditional modal analysis techniques, the proposed method proves to be more sensitive to structural alterations, even when the changes in modal properties are minimal. This characteristic is particularly advantageous for detecting early-stage damage, which might remain undetected using conventional modal-based approaches. However, a critical requirement of the methodology is the prior knowledge of the frequency bandwidths in which the bridge modes are located. This information is essential for selecting the appropriate DWT decomposition levels and computing the mean frequency in correspondence with them. Without this step, the analysis may be influenced by external loads rather than by structural dynamics, potentially leading to misinterpretation of the results. Overall, the findings of this study demonstrate the potential of the proposed DWT-based damage detection approach as an effective tool for structural health monitoring.

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