1st Latin-American Workshop on Structural Health Monitoring
LATAM-SHM 2023
December, 5-8 2023

BRIDGE DAMAGE DETECTION BY VARIATIONAL MODE DECOMPOSITION AND PCA OF TRAFFIC-INDUCED VIBRATIONS UNDER ENVIRONMENTAL VARIABILITY

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Key words: Damage Identification, Bridges, Environmental Variability, Instantaneous Phase Difference (IPD), Variational Mode Decomposition (VMD), Principal Component Analysis (PCA), Hilbert-Huang Transform (HHT).

Abstract. The environmental and operational influence is still a challenging problem owing because they mask structural damage in civil structures such as bridges. However, advances in signal processing and new artificial intelligence and machine learning tools make it possible to derive more robust and accurate methodologies for damage detection and location. This study proposes a novel bridge damage feature by combining the advantages of variational mode decomposition (VMD), Hilbert Transform (HT) and principal component analysis (PCA) algorithm in the presence of environmental variability and using the non-stationary traffic induced vibration. The proposed methodology considers three steps to analyze the dynamic response. The first step is to pre-process the vibration data (accelerations) using VMD, so the raw data is decomposed into a number of intrinsic mode functions (IMF). The second step is to apply the HT to the decomposed IMFs. Finally, Instantaneous Phase Difference (IPD) is obtained and used as damage indicator. PCA is applied to the IPD in order to eliminate the environmental influence and define appropriate criteria for damage detection avoiding false alarms. This methodology is applied to the case of a numerical model of a continuous bridge, showing promising results for damage detection and location under varying environmental and operational conditions.

1 INTRODUCTION

Bridges are an important part of the global road infrastructure, and they are designed to withstand the demands and design requirements requested. In addition, the structure can be affected due to its lack of maintenance and even due to external loads that were not considered during its design. Bridges, during their service period, are subjected to external conditions and loads that can cause aging and even sudden collapse [1]. Likewise, the lack of maintenance generates its deterioration and as a consequence its initial static and dynamic load capacity is reduced, which generates unplanned responses to any external factor [2]. On the other hand, structural health monitoring (SHM) in bridges allows continuous monitoring and detection of structural damage to prevent the aforementioned consequences [3]. In this sense, it is necessary to address the problem of identifying structural damage in bridges and seek innovative solutions that improve the effectiveness and efficiency in the evaluation of bridges. Nowadays, artificial intelligence plays a fundamental role by developing algorithms and models that can analyze data in a precise and automated way, identifying patterns of possible damage [4].

The authors [5] details that structural damage detection using big data in structural health monitoring in SHM can pose difficulties in terms of computational efficiency and ability to detect damage. This limitation is important due to the need for early and accurate damage detection to structures to ensure the safety and proper maintenance of infrastructures. [6] details that their promising technique has emerged from the combination of the Hilbert-Huang Transform (HHT) and the full Mode Empirical Decomposition with Adaptive Noise (CEEMDAN) together with Artificial Neural Networks (ANNs), this proposed methodology has been applied with success for damage detection in complex structures. [7] used Hilbert-Huang transform (HHT) and artificial intelligence algorithms to analyze vibration signals and obtain characteristics that indicate the presence of damage in real and numerical bridges. In [8][9] the vibration-based method (VBM) is proposed to detect structural damage and evaluates a steel bridge, in addition the author investigates different signal decomposition techniques and finds that the Improved Completed Ensemble Empirical Mode Decomposition with Adaptive Noise technique (ICEEMDAN) and the modal decomposition method variational analysis (VMD) are the most suitable to obtain dynamic properties and detect structural damage in bridges. In addition, the analysis of parameters such as instantaneous frequency, instantaneous amplitude and Hilbert spectrum is used to detect and locate damage in bridges. Also, [10] propose the use of marginal Hilbert spectrum and instantaneous phase difference as damage indicators. Likewise, it offers an innovative methodology to improve the detection of damage in bridges and proposes using equivalent damage load measurements of various types to obtain a comprehensive evaluation of these. This approach has the advantage of considering both the structural responses and the loading characteristics applied to the bridge, providing a more complete and accurate view of the structural health of the bridge. [11] propose an interesting method that is based on the use of the marginal Hilbert spectrum (MHS) and the instantaneous phase difference (IPD) as indicators of total damage in bridges. This methodology differs from traditional damage assessment methods by providing a non-invasive, near real-time assessment of the bridge structure.

The mentioned techniques and tools play a crucial role in identifying structural damage in bridges. These techniques, such as the use of artificial intelligence algorithms and numerical modeling with finite elements, offer great precision and effectiveness in detecting damage, allowing preventive measures to be taken in a timely manner. Additionally, these tools save time and resources by streamlining the detection process and optimizing preventative maintenance. They also improve decision-making by providing objective and quantitative information on the status of bridges, taking advantage of the advantages of automation and data analysis in the management of infrastructures such as bridges. From the above, the present research shows an innovative method of damage detection through variational mode decomposition (VMD), the Hilbert transform (HT) and the principal component analysis

(PCA) algorithm in the presence of environmental variability and uses vibration induced by non-stationary traffic. The flowchart used in this research can be seen in Figure 1.

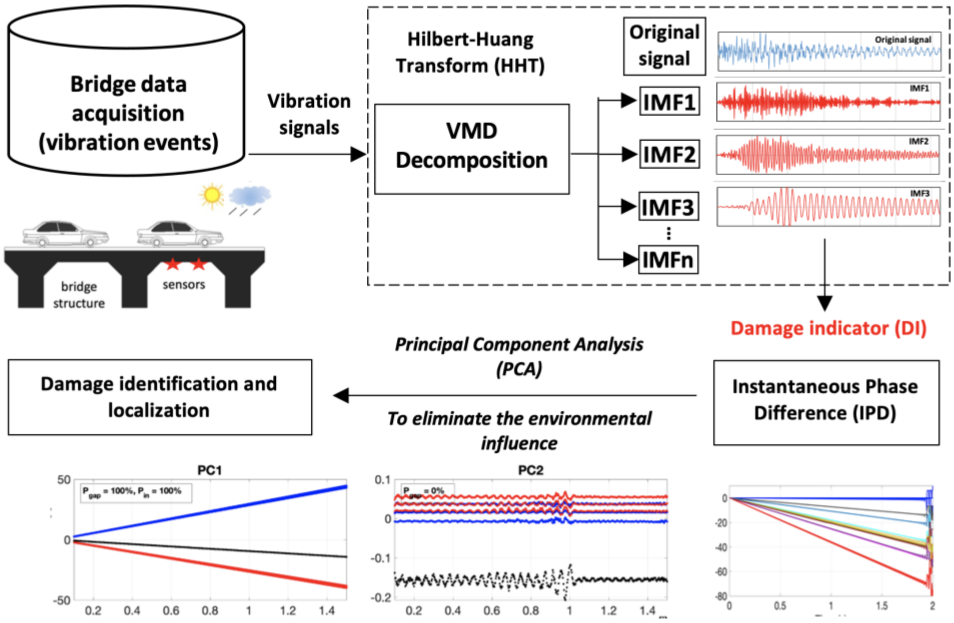


Figure 1: Flowchart of the proposed method.

2 MATHEMATICAL FORMULATIONS

2.1 Variational Mode Decomposition

The Variational mode decomposition (VMD) method is the latest quasi-orthogonal multi-scale signal processing tool where the input signal is decomposed into different band-limited IMFs. the essence of the VMD uses Hilbert transformation to solve the marginal spectrum as no modal aliasing effect and is sensitive to noise [12]. The variational problem can be solved by Equation 1 and 2.

$$\min_{\{u_k\},\{\omega_k\}} \left\{ \sum_k \left\| \partial_t \left[\left(\delta(\mathrm{t}) + \frac{j}{\pi t} \right) * u_k(\mathrm{t}) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \tag{1}$$

$$\text{Subject to } \sum_k u_k = f \tag{2}$$

Where u_k is the *k-th* IMF and ω_k = center pulsation around which the *k-th* IMF is mostly compact, δ is the Dirac distribution and f is the original signal. The bandwidth of each mode is estimated by the squared H^1 Gaussian norm of its shifted signal with only positive frequencies. Then, a quadratic penalty and Lagrangian multipliers λ are introduced to transformed into an unconstrained optimization problem.

2.2 Hilbert-Huang Transform

The Hilbert–Huang transform (HHT) is another type of signal processing method that is applicable for nonstationary and nonlinear signals to decompose intrinsic mode functions (IMF) [13]. In the present study, HHT will be used as a combination of two methodologies, namely, variational mode decomposition (VMD) and Hilbert transform (HT). Having obtained the IMF components from time history $x(t)$, the second step of the HHT method is implemented by performing the HT to each IMF component $c_n(t)$. The Hilbert transform of a real-valued time domain signal $c(t)$ is another real-valued time domain signal, it can be denoted by $\tilde{c}(\mathrm{t})$, such that $z(\mathrm{t}) = \mathrm{c}(\mathrm{t}) + \mathrm{i}\,\tilde{c}(\mathrm{t})$ is an analytic signal. The subscript in $c_n(t)$ is dropped for simplicity, so that the following equation 1 can be written:

$$\tilde{c}(\mathrm{t}) = \int_{-\infty}^{\infty} \frac{c(\mathrm{k})}{\pi(\mathrm{t}-\mathrm{k})} dk \tag{3}$$

Besides, in this study, the Instantaneous Phase Difference (IPD) will be used for damage identification and localization. The authors [14][15] developed the instantaneous phase obtained with the HHT called $\theta(t)$ in order to represent the phase of travelling structural waves of a dynamically measurable quantity, such as the acceleration, strain, or displacement. $\theta_p(t)$ denotes the instantaneous phase at a particular location p on the bridge structure. If a point o on the bridge is chosen as a reference point, then the phase function relative to this reference point o can be expressed by Equation 4, where the instantaneous relative phase $\varphi_p(t)$ is referred to state of a bridge at the point p. Besides, due the changes in the dynamic conditions of the bridge that are caused by potential damages, the $\theta_p(t)$ will reflect this behavior as a change on the speed at which energy travels through the bridge.

$$\varphi_p(\mathrm{t}) = \theta_p(\mathrm{t}) - \theta_o(\mathrm{t}) \tag{4}$$

2.3 Principal Component Analysis

PCA is a multivariate statistical data mining method used to reduce multidimensional data sets to a lower number of dimensions, and thus, the resultant factors provide a summary of the original data [16]. In this paper, PCA is used to extract the differences and similarities in the original data set rather than reducing the dimensions of the original data set. In the equation 5, Z denotes a nxp data set of n damage sensitivity features collected from p observations with $n<p$, and the instantaneous phase is chosen as the sensitive parameter, this index is represented by n and p represents the amount of time the instantaneous phase is collected.

$$Z = \begin{bmatrix} X_{1,1} & \cdots & X_{1,\mathrm{p}} \\ \vdots & \ddots & \vdots \\ X_{\mathrm{n},1} & \cdots & X_{\mathrm{n,p}} \end{bmatrix} \tag{5}$$

In this paper, the instantaneous phase difference (IPD) varies with time, therefore a third and fourth dimension is included as k and I within the original PCA matrix that has its original form of $X_{n,m}$. Therefore, a four-dimensional data matrix $X_{n,m,k,l}$, is obtained having a large number of interrelated variables, as depicted in Figure 2. In this sense, several temperatures, modes, sensors and time samples can be correlated between them, and firstly the multidimensional array should be firstly unfolded to obtain a 2-D data matrix before the application of PCA.

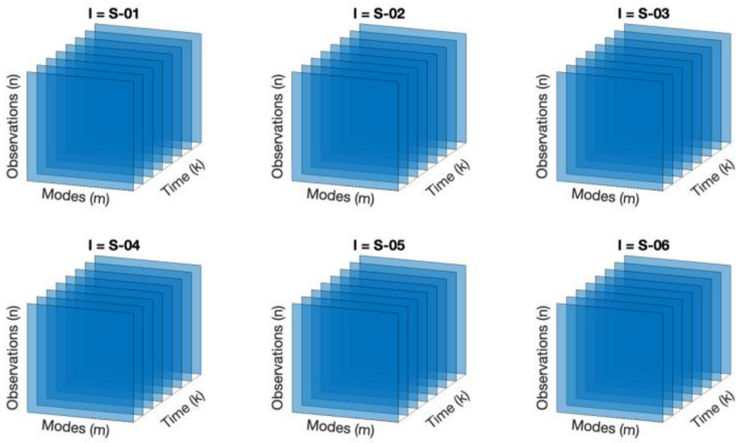


Figure 2: Data matrix with n = observations, m = damage parameters, k = time samples, l = sensors.

3 CASE OF STUDY - NUMERICAL STEEL BRIDGE

The numerical steel bridge has a total length L = 20m with two-span continuous beam with equal span lengths (L_1= L_2=10m), as can be shown in Figure 3a. This bridge has a rectangular cross section with 0.1m and 0.6m respectively, and the steel grade S235 presents a Young's modulus E = 215 GPa, Poisson's ratio $\nu = 0.3$, $\rho = 7850$ kg/m^3 at ambient temperature of T = 20ºC. The three supports present 10^6kN/m and 10^{15}kN/m for the horizontal and vertical stiffness respectively. This numerical bridge is reported in detail by [8][9][17].

On the other hand, the artificial damages imposed to bridge are shown in Figure 3b and it consists in reducing Young's modulus at the Gauss points on particular finite elements. Besides, six virtual sensors and damage scenarios grouped in two damage regions are considered to provide information about the nodal variables in both x (horizontal) and y (vertical) directions (Figure 3b). The location of sensors is presented in Table 1 and Table 2 shows the types of damage, for example damage 1 and damage 2 represent an area of two and four elements respectively, in addition, the damaged elements have a width of 0.05 m and the height ranges from 0.1 to 0.3 m.

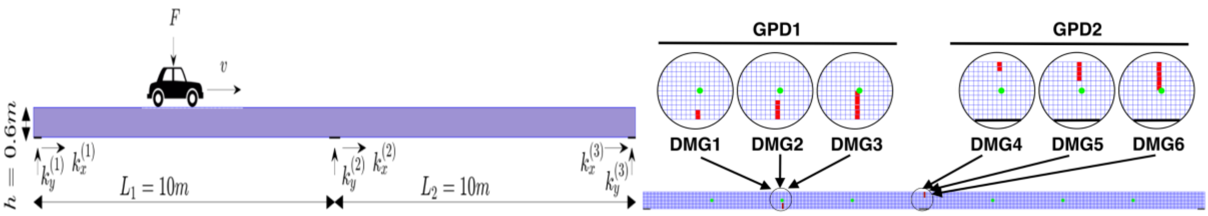


Figure 3: Numerical steel bridge (a) geometry (b) damage scenarios.

Table 1: Location of sensors along the numerical bridge.

Sensors	Description	Location along the neutral axis of the beam (y=0.3m)
S-01	at ¼L_1 left-hand	x = 2.5 m-
S-02	at ½L_1 left-hand	x = 5.0 m
S-03	at ¾L_1 left-hand	x = 7.5 m
S-04	at ¾L_2 right-hand	x = 12.5 m
S-05	at ½L_2 right-hand	x = 15.0 m
S-06	at ¼L_2 right-hand	x = 17.5 m

Table 2: Description of damage states in numerical bridge.

Damage scenarios	Mesh elements	Damage location
Undamaged (UND)	0	
Damaged 1 (DMG1)	2	at ½ L_1 from the left-hand support, starting from the bottommost edge
Damaged 2 (DMG2)	4	
Damaged 3 (DMG3)	6	
Damaged 4 (DMG4)	2	at ½ L_2 from the right-hand support, starting from the uppermost edge
Damaged 5 (DMG5)	4	
Damaged 6 (DMG6)	6	

4 DAMAGE DETECTION USING INSTANTANEOUS PHASE DIFERENCE (IPD)

The vibration signals obtained from the numerical bridge were evaluated and the number of modes m represents the IMF into which the original signal has been decomposed. In addition, the 10 observations of the extreme cases of environmental variability are obtained from the number of observations n=11 and were used to create the baseline. The IMF number m was obtained for all sensors, m=6 for sensors S-01, S-03, S-04 and S-06, and m=5 for sensors S-02 and S-05. For sampling, all modal parameters were obtained for 2 seconds and an output time of Δtout = 0.0025 sec was selected (equivalent to a sampling frequency of 400hz). This sampling frequency was used in order to obtain the first three bending mode shapes, where k=800. In addition, the VMD method is used to decompose the vertical accelerations for any temperature condition using the following parameters ε_r=1e-10, $\hat{\alpha}$ =500, τ=0.1, ε_a=0.1 and O=100000.

Figure 4 shows the instantaneous phase difference of each IMF for the undamaged state at the lowest temperature of -30ºC, these results are obtained by Equation 4. This figure shows the IPD for the baseline (red curves and blue) and the other monitored cases (color curves) for sensor 01. All damage scenarios shown in section 3 were considered. In addition, it can be seen that the monitored cases are within the baseline limits and at the end of the time interval shows the problem of boundary effects, for example in high frequency modes such as IMF1 and IMF2.

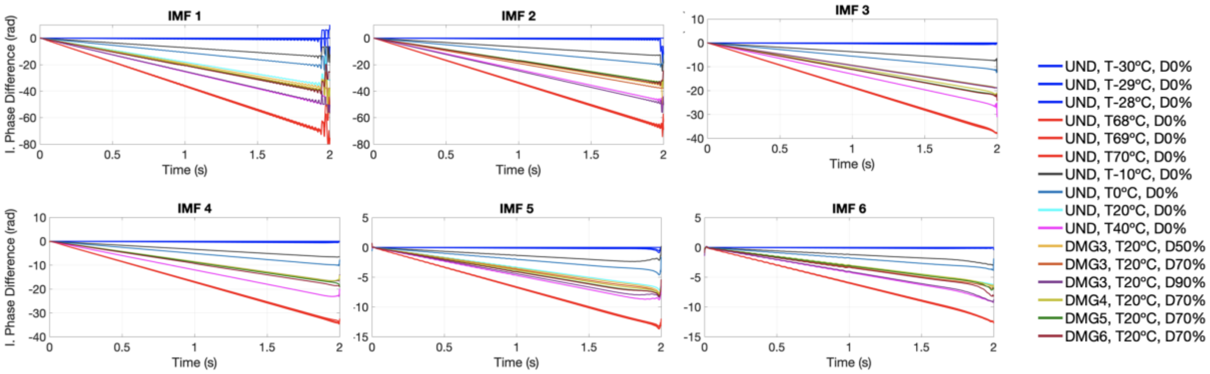


Figure 4: Instantaneous phase difference as damage indicator for damage scenarios and temperature conditions corresponding to each IMF obtained from sensor S-01.

The Figures 5 to 9 contain the instantaneous phase difference (IPD) for each IMF and for sensors 2 to 5 under temperature variations. In each result the same behavior is obtained as for sensor 1, with this technique, the IPD for all the sensors will have the similar order of magnitudes since their values does not depend from the other sensors, only in the number of IMFs considered in a particular sensor which is always the same for the undamaged and damaged scenarios. On the other hand, the sifting process is performed as well as the elimination of the singular IPD values at the end of the interval caused by the boundary effects problem.

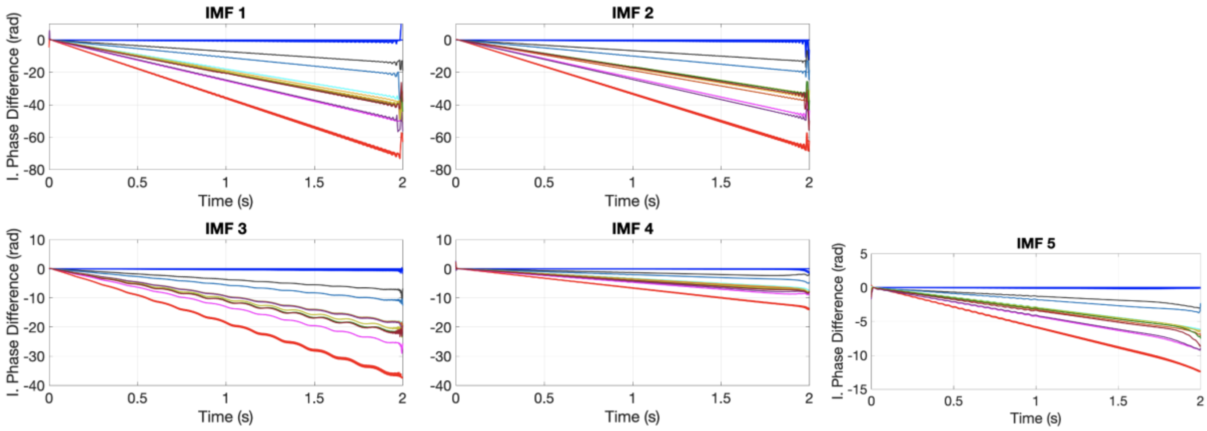


Figure 5: Instantaneous phase difference as damage indicator for damage scenarios and temperature conditions corresponding to each IMF obtained from sensor S-02.

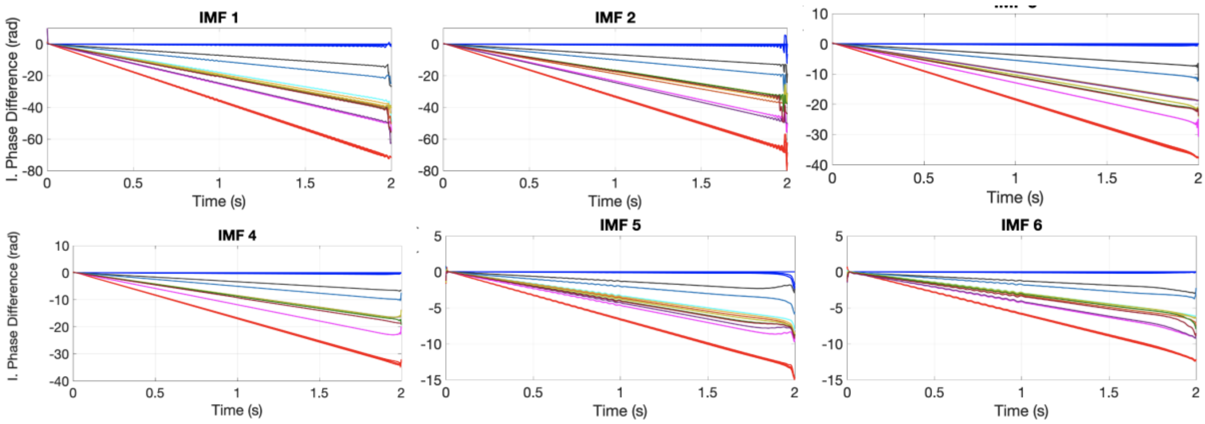


Figure 6: Instantaneous phase difference as damage indicator for damage scenarios and temperature conditions corresponding to each IMF obtained from sensor S-03.

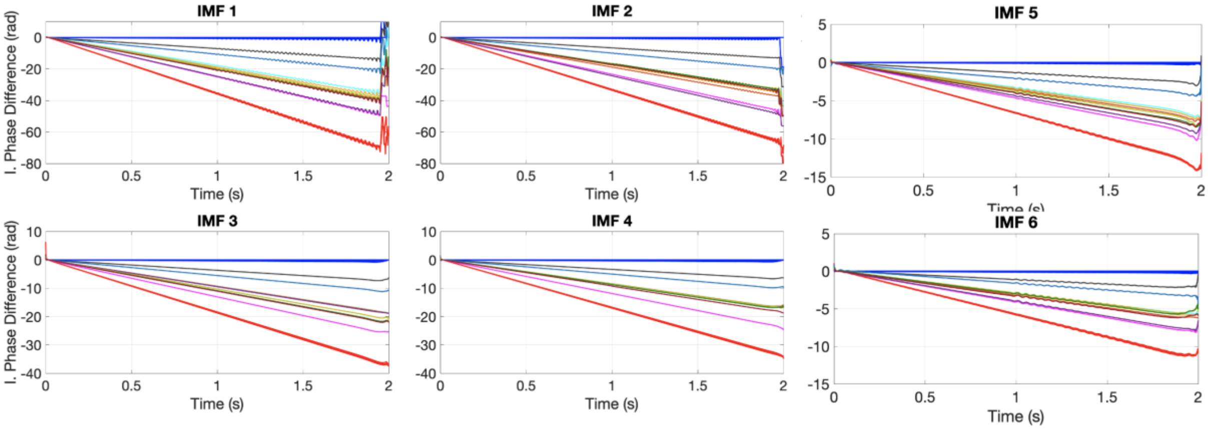


Figure 7: Instantaneous phase difference as damage indicator for damage scenarios and temperature conditions corresponding to each IMF obtained from sensor S-04.

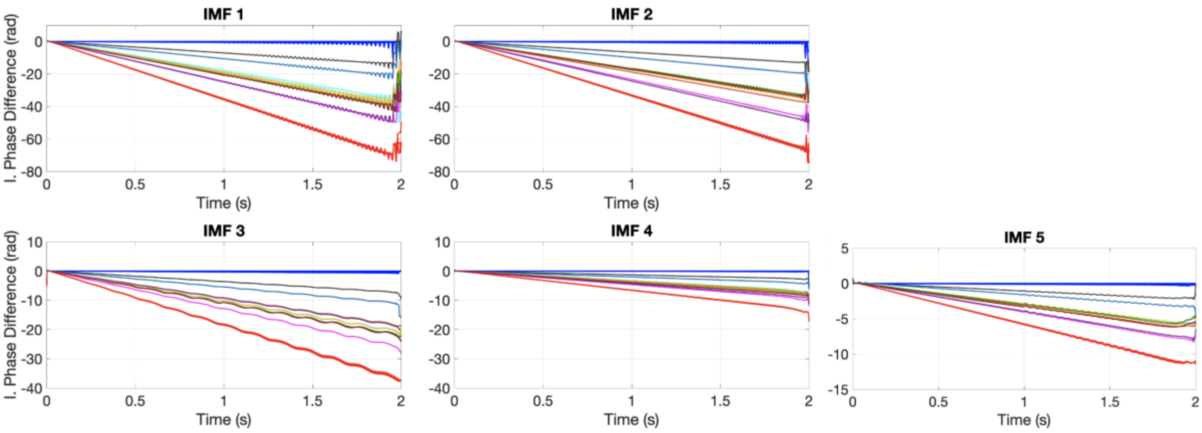


Figure 8: Instantaneous phase difference as damage indicator for damage scenarios and temperature conditions corresponding to each IMF obtained from sensor S-05.

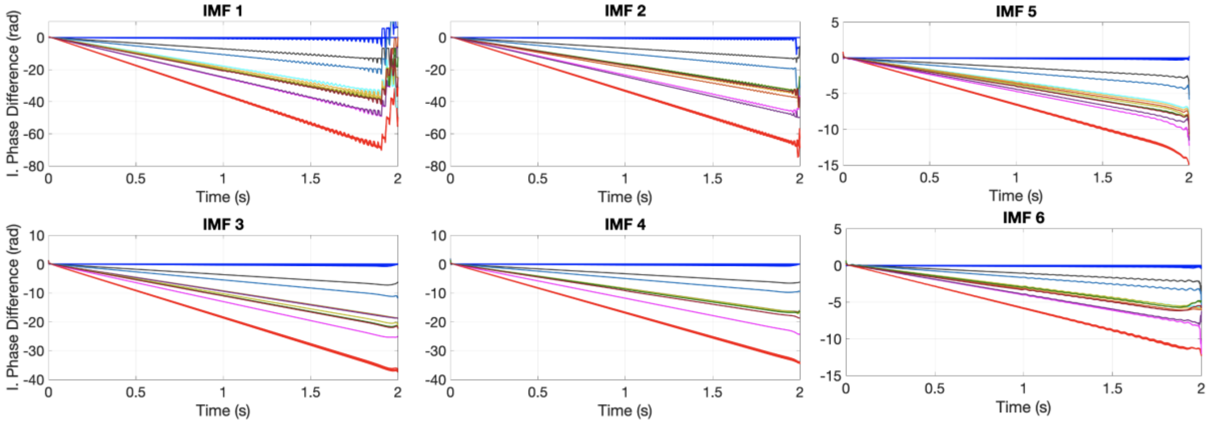
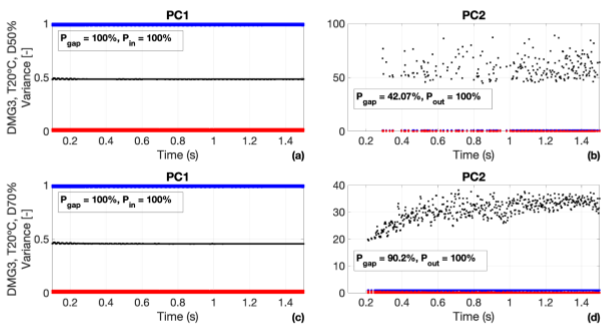
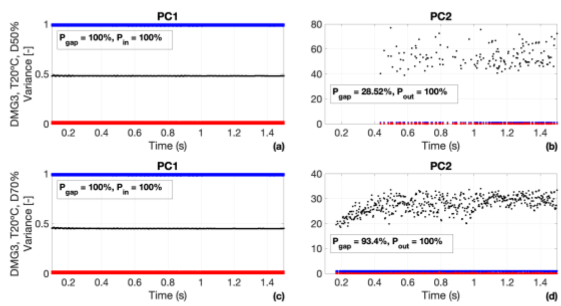


Figure 9: Instantaneous phase difference as damage indicator for damage scenarios and temperature conditions corresponding to each IMF obtained from sensor S-06.

On the other hand, the six modes (IMF) were taken into account for the application of the PCA algorithm in a time interval of 0.1 to 1.5 seconds, which is equivalent to 560-time samples. The Figures 10 to 12 shows the first and second principal components for the damaged cases of the GPD1 and GPD2, and an in-depth study was done for every sensor. This methodology mainly proposes that there must be a clear separation between the coldest and warmest limits and the baseline must meet this condition. Furthermore, the monitored case is represented by black dots. The baseline is standardized within 0 and 1, where 0 represents the limit of the highest temperatures (red dots) and 1, the upper limit of the lowest temperatures (blue dots). For all cases, in PC1 can be seen that all the points meet the condition for damage detection purposes, and all the monitored cases lie inside the temperature limits (100%). The monitored case tends to move to the hottest limit when the severity of damage increase, suggesting a rise in temperature when in fact there is not such a change. The influence of the highest and lowest-frequency modes in data set when the damage is severe make cause part of the damage to be interpreted as an increase in temperature. Regarding the damage evolution, it can be observed from the PC2 that increases when the severity of damage grows from 35% to 100%, while all the monitored cases lie outside the baseline limits (100%) for all cases, giving rise to damage alerts. It should be pointed out that, when damage increases, the monitored cases are no longer dispersed and become more constant over time. This corresponds to the fact that the three extreme cases with close temperatures are very similar.





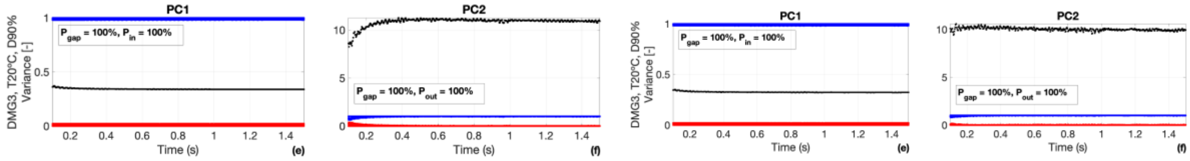


Figure 10: PC1 and PC2 regarding the IPD from sensor S-01 and S-02.

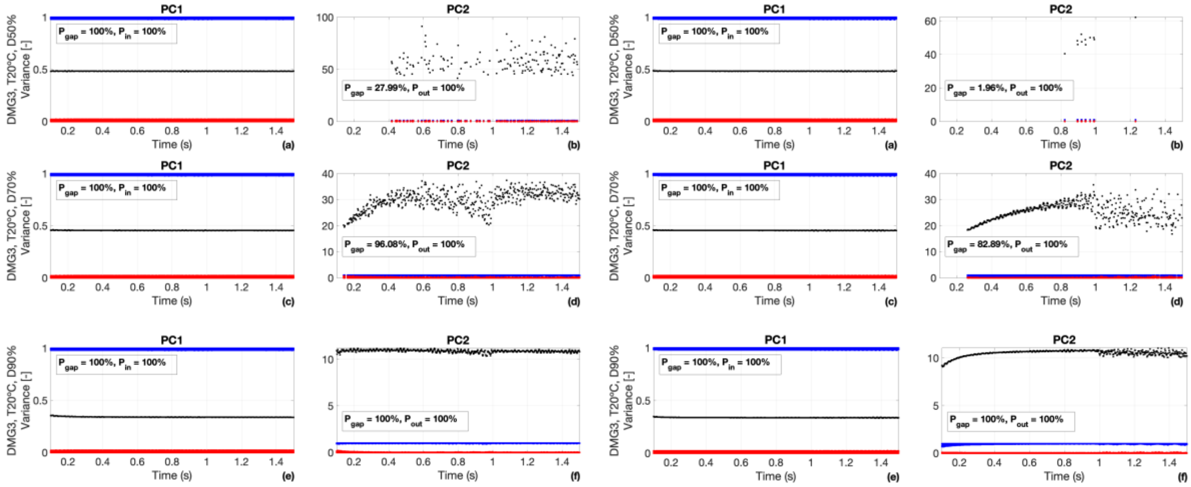


Figure 11: PC1 and PC2 regarding the IPD from sensor S-03 and S-04.

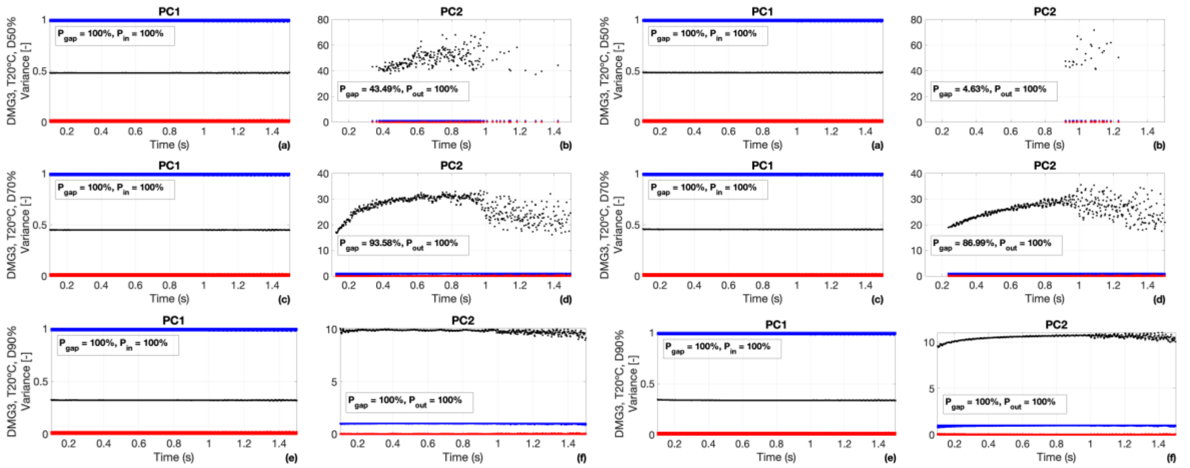


Figure 12: PC1 and PC2 regarding the IPD from sensor S-05 and S-06.

Finally, it can be noticed that as damage increases, more time samples between 0.2 and 0.8 seconds, approximately, meet the condition for damage detection. Therefore, it may suggest that the structural damage is located within this range, equivalent from 2 to 8 meters.

6 CONCLUSIONS

- The time-varying parameters were processed and decomposed by HHT and VMD respectively in order to obtain the instantaneous phase difference (IPD) for each IMF under different temperature conditions. Furthermore, the PCA algorithm had great performance in isolating the effects of environmental conditions, and in this way both methods together proved to be robust for the detection of structural damage in bridges.
- In the case of damage detection, only the first principal component (PC1) was retained in all undamaged cases, while the first two principal components (PC1 and PC2) were retained in all damaged cases since the baseline showed a clear separation between the extreme temperature cases at -30ºC and 70ºC, respectively.
- In all the undamaged cases under varying temperature conditions, the monitored case was found always between the baseline indicating that no damage occurs. Moreover, the evolution of temperature is observed from the monitored case while moving from the coldest limit to the hottest limit with increasing temperature.
- The instantaneous phase difference (IPD) was investigated for all sensors and it can be a good parameter to distinguish the temperature effects from damage effects, as well as to detect the severity of damage, but not to locate damage. The main drawback of PCA-method is that in some cases it can be difficult to choose the accurate extreme temperature for the baseline that guarantees an opposite behavior of the investigated variables.

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