Damage Sensitivity Evaluation of Vibration Parameters Under Ambient Excitation

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Abstract. Traditionally, damage detection techniques in bridges have focused on the use of modal-based damage features as they are supported by a well established theoretical base and can be directly related to changes in stiffness. However, modal-based damage features can also be difficult to extract from noisy data and thus their application may require initial large amplitude excitation, in the form of impact tests on closed bridges, to extract an accurate and full modal response. Furthermore, as damage detection and identification methodologies evolve to account for more and more variables, yet still fail to make the breakthrough into industrial applications, there may be an argument to reassess the selection of features used as inputs to these methodologies. Following some recent investigations that discovered a correlation between certain vibration parameters and bridge condition, the present study expands this inquiry by examining the level of damage sensitivity exhibited by various vibration parameters under more scrutiny. Initial sections of this paper outline the vibration parameters to be assessed and the damage detection algorithms employed. The paper finishes with the assessment of the chosen vibration parameters by using vibration data from a progressively damaged bridge subjected to ambient excitation. The paper also suggests a methodology that can be implemented to reduce uncertainty regarding ambient excitation sources.

Keywords: Damage detection \cdot Damage features \cdot Vibration parameters \cdot Structural health monitoring \cdot Outlier detection

1 Introduction

Damage detection and identification methods are increasingly considered to be a more objective approach to assessing bridge condition than visual inspections, which suffer inconsistencies due to inspector competency and differ in methodology from country to country [[1\]](#page-11-0). Although there are many advanced methods of damage detection now available, there still seems to be poor agreement on the optimal damage feature to use. Many damage features suffer from over sensitivity to external conditions, while others are difficult to extract accurately in ambient conditions. The optimal damage feature should be easily extracted, sensitive to damage and insensitive to external variability. The socio-economic value of the bridge is also a factor, as more valuable structures may be assessed using many sensors coupled with advanced analysis methodologies.

© Springer International Publishing AG 2018 J.P. Conte et al. (eds.), Experimental Vibration Analysis for Civil Structures, Lecture Notes in Civil Engineering 5, https://doi.org/10.1007/978-3-319-67443-8_21 However, the vast majority of bridge structures are of lower socio-economic value and thus require a simple and effective methodology that is cost effective. The present study investigates the level of damage sensitivity of a number of vibration parameters that are relatively simple to extract and assess. Data from a progressive damage test conducted on the S101 Bridge in Austria is used to test the damage sensitivity of the chosen vibration parameters. The associated uncertainty related to ambient excitation load sources is also addressed within by the incorporation of the Minimum Covariance Determinate estimator to the outlier detection algorithms.

2 Damage Features: Vibration Parameters

This study aims to explore the possibility of utilizing vibration parameters as damage features in ambient conditions. A number of vibration parameters have been identified that may attain some degree of damage sensitivity. The chosen vibration parameters assessed herein are: RMS Acceleration; Cumulative Absolute Acceleration; Arias Intensity; Peak-to-Peak Acceleration; and Vibration Intensity measured in Vibrars.

For the parameters RMS Acceleration and Cumulative Absolute Acceleration, they are measures of vibration amplitude across a specified time scale. The RMS Acceleration is simply the root mean square of the acceleration time history, and may attain some degree of damage sensitivity when a bridge is subjected to ambient excitation, as a persistent increase in the acceleration RMS may indicate that the structure is having to dynamically resist ambient loading more often due to the fact that it is losing the structural ability to resist the ambient sources of load in a more static and stable manner. Likewise, the Cumulative Absolute Acceleration, being the sum of all absolute acceleration values over a time window, may also indicate the structure's need to act in a more dynamic manner due to structural decline. It should be noted that these parameters are most likely to be of value in ambient conditions, where the sources of loading are Gaussian in nature.

Arias Intensity, defined by Arias [[1\]](#page-11-0), is a vibration parameter that is generally used to describe an earthquake's vibrational energy over its total duration. As the energy content of an earthquake is proportional to the square of the acceleration, Arias Intensity incorporates this by calculating the scaled integral of the squared acceleration response. Arias Intensity is commonly used as an indicator of an earthquake's damage potential both from its total cumulative value and also via the max slope of its cumulative series. In the present study, the total Arias Intensity will be used to assess the bridge vibration energy over time and if this changes with damage.

$$
I_A = \frac{\pi}{2g} \cdot \int_0^\infty a(t)^2 dt \tag{1}
$$

In the case of current investigation into the damage sensitivity of vibration intensity measured in vibrars, this stems from previous literature by Casas and Rodrigues [[3\]](#page-11-0), who discussed the relationship between vibration intensity and structural condition of bridges. The variable "vibration intensity" was first proposed by Koch [[4\]](#page-11-0) to be correlated to the degree of damage in buildings. The rationale behind this connection lies

in the fact that the mean-square value of the acceleration varies with frequency $\{a^2(f)\}$ and damage potential of the vibration falls off with frequency, therefore, it is reasonable to assume that damage caused by inertia forces is proportional to $\{a^2(f)/f = I(f)\}\$. In a simply harmonic motion with an acceleration of amplitude a_0 , the term $\{a_0^2/f\}$ is called vibration intensity. The SI units are mm^2/s^3 and its non-dimensional (decibel) form is presented in Eq. (3), where I_s is a standard value, arbitrarily chosen to be 10 mm²/s³. Additionally, vibration intensity can be determined via displacement vibration though the relationship presented in Eq. (4) . The units of V defined in this way are called 'Vibrars'.

$$
I = a_0^2/f \tag{2}
$$

$$
V = 10 \log 10(I/I_S) \text{ (where } I_S = 10 \text{ mm}^2/\text{s}^3 \text{)}
$$
 (3)

$$
V = 10 \log(160\pi^4 a^2 f^3)
$$
 (4)

Results from the aforementioned study by Casas and Rodrigues [\[3](#page-11-0)], and subsequently revised in Moughty et al. [[5\]](#page-11-0), found that the correlation between maximum vibration intensity measured in Vibrars and bridge condition was weak, however, the authors noted that the damage index, developed via FEA calibration, may have accounted for the poor correlation, as much of the data used to calibrate the FEA models was dated or unavailable. Conversely, the same study found a relatively strong correlation between max Peak-to-Peak accelerations and bridge condition. In the same sense that RMS acceleration and Cumulative Absolute Acceleration may indicate structural decline through increased dynamic behavior, max Peak-to-Peak acceleration may demonstrate likewise.

Unlike the other vibration parameters assessed in this study, vibrars are a function of not only vibration amplitude, but frequency as well. This allows for greater depth of assessment, as specific frequency ranges can be targeted for analysis. In the study by Casas and Rodrigues [[3\]](#page-11-0), only the max vibrar values were extracted, however the present study expands this to include the vibrar values associated with the first four natural frequencies also, specifically, the first two bending modes and the first two torsional modes. The vibrar extraction process entails the conversion of the acceleration time histories to the frequency domain and subsequently scaling the values based on the relationship expressed in Eq. (3). For improved accuracy of extraction, Hanning windows were employed in two stages; firstly, a low number of long windows with an overlap of 50% were applied to improve frequency resolution and extraction, while a larger number of windows were employed to optimize the amplitude resolution and extraction. However, caution is advised with this approach as the number of windows chosen may affect results, as too few windows makes for noisy amplitude values, while too many will raise the noise floor and thus the amplitude values also.

3 Outlier Detection Methodologies

For the purposes of demonstrating the raw damage sensitivity associated with each vibration parameter, the standard Mahalanobis Squared-Distance (MSD) outlier detection algorithm is employed for its simplicity which will allow for a better examination of the vibration parameters' damage sensitivity, without enhancement from more advanced pattern recognition techniques. However, in addition to assessing the damage sensitivity of certain vibration parameters, the present study also assesses the performance of some other outlier detection techniques, namely Principle Component Analysis (PCA) and Singular Value Decomposition (SVD).

A further addition to the present study is the incorporation of the Minimum Covariance Determinate (MCD) estimator to the aforementioned outlier detection methodologies to increase performance robustness and mitigate the uncertainty surrounding the sources of ambient excitation.

3.1 Mahalanobis Squared-Distance

The MSD [\[6](#page-11-0)] is a common technique used to detect outliers in multivariate data by using the mean and covariance of a training dataset, which in the present study is that of the undamaged condition. The MSD is determined as shown in Eq. (5), where ${X}_{\zeta}$ is the potential outlier, $\{\bar{X}\}\$ is the mean of the training data and $[\Sigma]$ is the covariance matrix of the training data.

$$
D_{\zeta} = \left(\{X\}_{\zeta} - \{\bar{X}\}\right)^{T} [\Sigma]^{-1} \left(\{X\}_{\zeta} - \{\bar{X}\}\right) \tag{5}
$$

3.2 Principle Component Analysis

PCA is a technique used primarily to reduce the dimensionality of complex data sets while retaining a high level of relevant detail that can be more easily observed and quantified. PCA works by initially finding the maximum variance of the dataset, which it uses as its first principle component, and continuing in an orthogonal manner to associate subsequent principle components to the next largest variance. By doing this, PCA can discard the linear combinations of the data that contribute least to the overall variance of the data set. As an outlier detection technique, a covariance matrix $[\Sigma]$ is obtained for the training data and subsequently decomposed using the calculated principle components $[\Lambda]$ as shown in Eq. (6). Test data $\{x\}$ can be scored using the transformation matrix $[A]^T$ and the component-wise means of the training data $\{\bar{x}\}$, as shown in Eq. (7) [[7\]](#page-11-0).

$$
[\Sigma] = [A][\Lambda][A]^T \tag{6}
$$

$$
\{z\}_i = [A]^T (\{x\}_i - \{\bar{x}\})
$$
 (7)

3.3 Singular Value Decomposition

SVD is a technique used to transform rectangular matrix of the undamaged training data [M] into two orthogonal matrices [U] and $[V]$ ^H and a vector containing the singular values $[A]$, as shown in Eq. (8), which is the same decomposition method as used in Eq. ([6\)](#page-3-0). For outlier detection, a new matrix $[M']$ is obtained by inserting a vector of data from a damaged or unknown condition state $\{y\}$ at the end of an undamaged matrix $[X]$ (Eq. (9)). Equation (8) is repeated for $[M']$ and damage is assessed by finding the difference between the original and updated singular values [\[7](#page-11-0)].

$$
[\mathbf{M}] = [U][\Lambda][V]^H \tag{8}
$$

$$
[M'] = [[X], \{y\}_i] \tag{9}
$$

3.4 Minimum Covariance Determinate

A further addition to the present study is the incorporation of the Minimum Covariance Determinate (MCD) estimator to the aforementioned outlier detection methodologies to increase performance robustness and mitigate the uncertainty surrounding the sources of ambient excitation by finding outliers within the training data and removing them. As the environment conditions remained constant through the damage test on the S101 Bridge and the bridge was no longer in use, it would be generally considered acceptable to assume a Gaussian distributed source of ambient loading and that all recorded vibrations were due to this load source. However, due to the fact that one lane under the bridge was still in operation throughout the test and construction work was in progress nearby, this cannot be assumed. This leaves a case where the undamaged vibration data used to train the various outlier detection algorithms may contain outliers itself due to passing traffic or construction vehicles. The inclusion of these outliers in the training data may have a substantial negative impact on the subsequent test/damaged data results, particularly if the outliers are significantly dissimilar to the majority of data.

The MCD is employed in the present study via the FAST MCD algorithm [\[8](#page-11-0)] which accomplishes its objective of removing erroneous data by first determining the subset of data whose covariance matrix has the lowest possible determinant to that of the total dataset. This process takes multiple iterations to complete and requires each subset assessed to contain at least 50% of the overall dataset, although in the present study the limit was increased to 75% for conservatism. Once the MCD finds the data points that contribute most to abnormal variance compared to the remaining data, it returns newly updated mean and covariance values that can be used directly in the MSD, as Dervilis et al. [[9\]](#page-11-0) demonstrated. Additionally the new covariance matrix from the MCD can be used in the training phase of PCA via Eq. [\(6](#page-3-0)), in addition to updating the component-wise means $\{\bar{x}\}\$ in Eq. [\(7](#page-3-0)). Furthermore, as the MCD identifies the erroneous data points, the latter can be removed before training the SVD.

4 Test Data: Progressive Damage Test of the S101 Bridge

The S101 Bridge was a post-tensioned three-span flyover near Vienna in Austria that was constructed in the early 1960's. The main span had a length of 32 m, while the two side spans had lengths of 12 m each. The cross-section of the bridge deck was 7.2 m wide and was designed as a double-webbed t-beam, whose webs had a width of 0.6 m. The height of the beam varied from 0.9 m in the mid-span to 1.7 m over the piers, as can be seen in Fig. 1. In 2008, it was decided to replace the S101 Bridge due to insufficient carrying capacity and deteriorating structural condition being identified from visual inspection data. Additionally, the bridge did not meet its service requirements, as the structure did not fit into the overall traffic and infrastructure concept for its location anymore.

Fig. 1. S101 Bridge longitudinal section [[10](#page-11-0)]

A progressive damage test was conducted on the S101 Bridge across three days in 2008 (December 10th to December 13th). The artificial damage was imposed though the completion of a number of sequential actions, which are presented in Table [1](#page-6-0). Overall, the damage applied can be divided into two main stages, with the first comprising of a simulated pier foundation settlement conducted on the bridges north side only, and the second comprising of a bridge deck stiffness loss through the severing of four pre-stressed tendons.

The bridge was closed to traffic during the progressive damage test, meaning that excitation was mainly ambient, although one traffic lane beneath the bridge was in use throughout the test which resulted in vibrations being transmitted through the foundations. Additionally, construction work was also in progress nearby that used heavy machinery and affected the vibratory response of the bridge at times, particularly during the cutting of the first pre-stressed tendon when it was noted that a vibrating impact roller was in operation close by. These additional sources of excitation add a level of uncertainty to the vibration data as no specific information on traffic volume was recorded. As for environment sources of excitation, very little temperature variation was observed throughout the test duration as sub-zero temperatures were kept within a 3–4° range due to heavy cloud cover that did not clear during daylight hours.

It is worth noting that prior to the artificial pier settlement stage of the damage test, the deck was hydraulically supported by a temporary supporting pier that was loaded to the original pier's supporting force of 120t. This allowed for greater control and safety when cutting through the pier, while also allowing the pier to be lowered quickly in 1 cm stages. The initial plan was to lower the pier in 5 steps to a maximum of 5 cm, however, due to increased cracking in the supporting t-beam, the pier settlement was halted at 3 cm, after which compensating plates were inserted under the pier before being hydraulically lifted back to its original position. Although subsequent damage actions were performed on the bridge, which entailed the severing of four pre-stressed tendons (see Table 1), the present study focuses only on the pier settlement damage actions.

Vibration data was recorded by numerous accelerometers located on the bridge deck, with a sample rate of 500 Hz. Vibration recordings from the sensors did not cease throughout the progressive damage test, even recording during the night. For the present study, the measured data was discretized into 66 s time-segments of 33,000 samples each.

Damage	Start time	End time	Description of damage
state			actions
1^{a}	10.12.2008 05:16 PM	11.12.2008 07:13 AM	Undamaged
$2^{\rm a}$	11.12.2008 07:13 AM	11.12.2008 10:21 AM	North-western column cut
			through
3 ^a	11.12.2008 10:21 AM	11.12.2008 11:49 AM	First step of lowering bridge pier (1 cm)
$4^{\rm a}$	11.12.2008 11:49 AM	11.12.2008 01:39 PM	Second step of lowering
			bridge pier (2 cm)
5^{a}	11.12.2008 01:39 PM	11.12.2008 02:45 PM	Third step of lowering
			bridge pier (3 cm)
6 ^a	11.12.2008 02:45 PM	12.12.2008 05:52 AM	Compensating plates are. inserted
$7^{\rm a}$	12.12.2008 08:04 AM	12.12.2008 01:12 PM	Column returned in original position
8	12.12.2008 01:12 PM	12.12.2008 03:03 PM	First tendon severed
9	12.12.2008 03:03 PM	13.12.2008 05:44 AM	Second tendon severed
11	13.12.2008 05:44 AM	13.12.2008 10:08 AM	Third tendon severed
12	13.12.2008 10:08 AM	13.12.2008 11:14 AM	Fourth tendon partially severed

Table 1. List of measurements recorded during the S101 Bridge progressive damage test

Note^a: Damage states highlighted in BOLD were chosen for damage detection assessment as part of this paper's work.

5 Results

Results of the present study are divided into two sections: (1) results of the damage sensitivity assessment of chosen vibration parameters, (2) comparison of outlier detection algorithm performance with and without the incorporation of MCD as an initial step to remove outliers from the training data for the purposes of reducing uncertainty regarding ambient loading.

5.1 Vibration Parameter Damage Sensitivity Assessment

The following results have been obtained via the MSD outlier detection algorithm which used random selection of 70% of the undamaged data as a training set and 30% for validation before being applied to the damaged data. A threshold value of 95% was chosen throughout. Vibration parameters were extracted from four sensor locations on the main span of the bridge deck, specifically, from the quarter point, center point, three-quarter point and from next to the damaged pier. Parameters were combined across all four sensor locations to increase damage sensitivity and outlier detection robustness. As previously mentioned, the data assessed is from the pier settlement damage actions only, which entail the cutting, lowering and returning of the pier in stages that can be clearly identified in the following plots. Note that the last stage in the plots represents two stages as denoted in Table [1](#page-6-0), which contain vibration parameters associated with the insertion of compensatory plates and with the pier being returned to its original position.

Figures 2, [3](#page-8-0) and [4](#page-8-0) present the results of the five vibration parameters: RMS Acceleration; Cumulative Absolute Acceleration; Arias Intensity; Peak-to-Peak Acceleration; and Maximum Vibration Intensity measured in Vibrars (Max across all frequencies). All parameters demonstrate some degree of damage sensitivity, with Cumulative Absolute Acceleration and Arias Intensity performing best, as can be seen from the MSD values on the Y-axis. Interestingly, the Max Vibrars (Fig. [4](#page-8-0)) performed worst, however, as Vibrars are a function of frequency, a more refined assessment can be made by targeting specific frequency ranges.

Figures $5(a)$ $5(a)$, (b) and $6(a)$ $6(a)$, (b) each present the results of the Vibration Intensity measured in Vibrars associated with the first four natural frequencies for each sensor location. The damage sensitivity of Vibrars is considerably improved in this manner, as clear definition between damage actions is visible.

Fig. 2. RMS acceleration (a) and cumulative absolute acceleration (b) from four sensor locations combined

Fig. 3. Arias intensity (a) and max peak-to-peak acceleration (b) from four sensor locations combined

Fig. 4. Maximum vibration intensity (vibrars) from four sensor locations combined

Fig. 5. Vibration intensity (vibrars) associated with the first four natural frequencies for sensors located at south quarter point (a) and center point (b)

Fig. 6. Vibration intensity (vibrars) associated with the first four natural frequencies for sensors located at north quarter point (a) and next to damaged pier (b)

Figure 7 presents the results of the Vibration Intensity measured in Vibrars associated with the first four natural frequencies combined across all four sensor locations, resulting in a total of 16 damage features. Excellent condition separation is achieved in this manner, with additional detail becoming visible, for instance, one can observe when the pier was fully cut through by the stepped separation in the red data, also when the pier was fully returned to its original position in the final section of data. Additionally, the individual lowering steps are amplified.

Fig. 7. Vibration intensity (vibrars) associated with the first four natural frequencies for all 4 sensor locations combined

5.2 Outlier Detection Performance and Robustness Assessment

The following results demonstrate the ability of the outlier detection algorithms MSD, PCA and SVD for discerning changes in structural condition. Additionally, the incorporation of the MCD estimator applied to the training data to remove outliers that may be associated with unknown eternal excitation sources is assessed also. All results herein are for the Vibration Intensity measured in Vibrars associated with the first four natural frequencies combined across all four sensor locations. Figure 8(a) and (b) present the MSD results for the standard MSD method (same as Fig. 7 but different scale) and the robust MSD method incorporating the MCD estimator. It is clear that the removal of outliers from the training data enhances the MSD performance. The removed outliers from the training data were reintroduced in the test data, and can now clearly be identified in Fig. $8(b)$ as outliers.

Fig. 8. Vibration intensity (vibrars) associated with the first four natural frequencies for all 4 sensor locations combined using standard MSD (a) and robust MSD incorporating MCD (b)

Figures $9(a)$, (b) and $10(a)$, (b) present the results from the PCA and SVD method, respectively. It can be seen that both methods are successful in determining condition variation, although not to the same level of clarity as conveyed by the MSD method. Also of note is that the incorporation of the MCD estimator improved the PCA performance significantly, but only slightly improved that of the SVD.

Fig. 9. Vibration intensity (vibrars) associated with the first four natural frequencies for all 4 sensor locations combined using standard PCA (a) and robust PCA incorporating MCD (b)

Fig. 10. Vibration intensity (vibrars) associated with the first four natural frequencies for All 4 sensor locations combined using standard SVD (a) and robust PCA incorporating SVD (b)

6 Conclusions

The present study investigated the damage sensitivity of a number of vibration parameters and determined that vibration parameters that are associated with vibration energy (squared amplitude of vibration) perform best, namely; Cumulative Absolute Acceleration, Arias Intensity and Vibration Intensity. This is presumably due to the fact that as the bridge is damaged, it needs to resist external loads using more kinetic energy as it attains less potential energy.

Vibration intensity assessed was calculated using the vibrar scale which weights the intensity magnitude depending on frequency. It was assessed by both extracting the overall maximum vibrar and by targeting specific narrow frequency ranges whereby the vibrar scale no longer had much effect. Judging by the significant difference in results between the max vibrars and the targeted narrow frequency range vibrars, it can be determined that the vibrar scale does not lend itself well to enhancing damage detection, and may in fact inhibit it.

As vibration intensity is a function of frequency and vibration energy, it attains a level of adaptability greater than the other vibrations parameters assessed that allows for multiple vibration intensity damage features to be extracted per time history. The results obtained from the targeted frequency ranges associated with the first four modes demonstrated that vibration intensity also attains a high level of damage sensitivity. It was also demonstrated that combining damage features across multiple modes and sensors considerably improves results.

All assessed outlier detection methodologies performed well, although MSD produced the highest resolution of structural condition variation. Additionally, the incorporation of the MCD estimator to the outlier detection algorithms successfully improved results by identifying and removing erroneous data from the training sets and helped to mitigate the uncertainty regarding external sources of excitation.

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