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Distinguishing Damage Effects from Temperature Effects for Damage Detection of Civil Structures

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ABSTRACT

A method is developed in this paper for damage detection of civil structures subjected to a varying temperature. A novel approach to create the baseline of the undamaged structure is proposed to consist of damage sensitivity features obtained at two extreme and opposite temperature conditions. To allow near-real time monitoring, new measurements can be added to the baseline one at a time to form new data sets, and Principal Component Analysis is proposed to be used to process each data set. Analyzing the first few principal components, damage effects can then be distinguished from temperature effects. The method is verified numerically on a truss structure model subjected to a varying temperature. The results demonstrate the ability of the proposed method to distinguish damage from temperature effects. Analyzing one measurement at a time without requiring a large set of measurements to be analyzed simultaneously, demonstrates that the method is able to perform near-real time monitoring. The novel approach of creating the baseline of the undamaged structure allows a rough indication of the temperature the structure is faced to, to be obtained without directly measuring the temperature condition. Damage progression can also be given from the proposed method which makes it advantageous for damage evolution monitoring.

1. INTRODUCTION

Civil structures of the likes of bridges and buildings that the society depends on, are in constant degradation due to the increase in population demand as well as the harsh environmental conditions they are faced to. As a result, Structural Health Monitoring (SHM), which aim is to monitor the current health conditions of structures,

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has drawn considerable attention among researchers during the past decades. SHM system monitors structures and alerts the authorities of any anomalies occurring in the structures so that appropriate measures can be taken to repair/replace defect structural components before more severe damages occur, hence increasing the safety and lifetime of these structures.

Researchers have been particularly active in developing methods for damage detection of civil structures which are mainly focused on analyzing the vibration properties (e.g., natural frequencies) of the structures that change when damages occur. However, even though these developed methods have been tested and validated using numerical and experimental model structures, difficulties arose in implementing them for real-time monitoring of in-service structures. The primary reason behind this is that, the environmental conditions (e.g., ambient temperature) the structures are faced to, also affect the vibration properties of the structures, which were not considered in most of the developed methods (Sohn 2007).

The ambient temperature the structures are faced to, was especially found to have a considerable influence on the vibration properties of the structures (Alampalli 1998, Fu and DeWolf 2001, Ni et al. 2005, Li et al. 2010, Zhou et al. 2010). For example, for the Alamosa Canyon Bridge, Cornwell et al. (1999) found out that the first, second and third natural frequencies of the bridge had a daily variation of 4.7%, 6.6% and 5%, respectively due to the ambient temperature change. For the Z24 Bridge in Switzerland, Peeters and De Roeck (2001) also reported a variation of the first four natural frequencies of the bridge with temperature. They found a bilinear relationship for most combinations of natural frequency and temperature (temperature of deck soffit, temperature of wearing surface, etc.). They suggested that this nonlinear relationship may be attributed to the asphalt layer which contributed to the stiffness of the bridge at temperature below 0 °C, while not playing any role at higher temperature. Desjardins et al. (2006) also studied the variations of natural frequencies of the Confederation Bridge with temperature. They reported an average variation of about 4.8% in the natural frequencies of the bridge for a temperature range of -20 °C to 25 °C. Thus, if the effects of the changing environmental conditions on the vibration properties which are commonly used as damage sensitivity features are not accounted for in damage detection methods, false damage alerts may occur.

To tackle the problem of the varying environmental conditions for damage detection, several approaches have been proposed in the literature. One of the proposed approach is to perform regression analysis between damage sensitivity features (e.g., natural frequency), and the environmental parameters (e.g., temperature) in which they were obtained (Peeters and De Roeck 2001, Worden et al. 2002, Dervilis et al. 2015). This approach creates a model that can predict the values of damage sensitivity features given the conditions the structures are faced to. Any large error in the prediction can then be attributed to damage. To perform this approach, measurements of damage sensitivity features obtained from a wide range of environmental conditions are required to form the baseline of the undamaged structure so that all possible conditions the structure may encounter can be captured. This approach also requires the damage sensitivity features and the environmental parameters to be gathered at the same time instance, hence introducing some practical difficulties. For example, although it is easy to capture the environmental parameters, selecting which parameters to measure may pose difficulties since different structures may be affected differently by different conditions, thus, past knowledge may not be reliable. Moreover, the locations for the placement of the sensors to capture these parameters may be difficult to choose, and to access (Kullaa 2002). Furthermore, after the baseline of the undamaged structure has been formulated using the parameters captured by the sensors, these sensors must remain at the same locations on the structure for operation (Yan et al. 2005). Any failure occurring in any of them may render the ability of the SHM system. Thus, due to all these aforementioned constrains, the use of this approach for damage detection under changing environmental conditions is limited.

Another common approach that has been proposed is to extract features that are sensitive to damage but less sensitive to the effects of the changing environmental conditions (Kullaa 2002, Cross et al. 2011). This approach has the advantage over the previous approach described in that the environmental parameters do not need to be measured, and only the damage sensitivity features are required for damage detection. Among all the techniques adopted, Principal Component Analysis (PCA), a multivariate statistical tool, has been widely used by researchers for data processing. For example, Manson (2002) proposed to apply PCA on damage sensitivity features data set and to perform an outlier analysis on the last principal components obtained, to indicate the presence of damage. The concept behind this method is that the first principal components, which account for most of the variances in the original data set, will account for the effects of the changing environmental conditions, while the following principal components, which account for the other minor variances, will account for other factors of the likes of damage. Thus, discarding the first principal components, the effects of the changing environmental conditions may be eliminated while the effects of damage may be retained. Yan et al. (2005) also used the same concept for damage detection under varying environmental conditions. They proposed to retain and use the higher variance principal components as a model to reconstruct the original data set so that the minor factors of the likes of damage can be eliminated. Then, by subtracting the newly formed data set from the original data set, a residual error can be obtained and be used to indicate damage. Any large residual error may then be attributed to the existence of damage. However, similar to the regression analysis approach, to perform this approach, it is also required to capture damage sensitivity features from a wide range of environmental conditions to construct the baseline of the undamaged structure so that it covers all possible conditions the structure may encounter. Therefore, developing a method that does not require the baseline to be constructed from a wide range of environmental conditions, will make SHM easier.

In this paper, since temperature was found to have considerable effects on vibration properties of structures, a method using PCA is developed to distinguish damage from temperature effects affecting damage sensitivity features for damage detection. A novel approach to create the baseline of the undamaged structure is proposed to consist of damage sensitivity features obtained at two extreme and opposite temperature conditions (e.g., temperature at -30 °C and at 70°C). Subsequent measurements that need to be monitored can then added one at a time to the baseline to form new data sets, and PCA is proposed to be used to process each data set. Analyzing the first few principal components, damage can then be distinguished from temperature effects. The method is tested for different undamaged and damaged cases on a truss structure subjected to a varying temperature to simulate a varying environmental condition. The results demonstrate the robustness of the proposed method in distinguishing between damage and temperature effects. Analyzing one measurement at a time without requiring a large set of measurements to be analyzed simultaneously, demonstrates that the method is able to perform near-real time monitoring. The novel approach of creating the baseline also allows a rough indication of the temperature the structure is faced to, to be obtained without directly measuring the temperature condition. Damage progression can also be given through the proposed method.

2. METHODOLOGY

This section introduces the proposed method for damage detection under changing temperature conditions. A brief introduction on PCA, which is used for data processing, is first given, followed by a visualization interpretation on how PCA can be used in the context of this study. Then, the damage detection method is described in detail with a summary of the procedures to follow, given at the end of this section.

2.1 Principal Component Analysis

Principal Component Analysis is a multivariate statistical technique used to highlight similarities and differences in a data set by finding patterns in the set. It is mainly used to reduce the dimensions of the original data set without losing much of the information (Smith 2002). It forms new variables which most characterize the variances in the original data set using linear combinations of each of the original variables (after mean centering) (Sharma 1996).

PCA can be applied to damage sensitivity features collected from civil structures subjected to varying temperature conditions to extract the main factors driving the variances in the damage sensitivity features. These factors may be attributed to the changing temperature conditions as well as damage of structural components. A brief description of the principle behind PCA is given below.

Consider a $\mathrm{n} \times \mathrm{p}$ data set $\mathbf{Z}$ composed of n damage sensitivity features of a structure collected from p observations. If for example, natural frequencies of the structure are chosen as the features, then n represents the number of frequencies selected, while p represents the number of time the natural frequencies are collected. To perform PCA on the damage sensitivity features data set, mean centering of the data set is first required. This is realized by subtracting the mean of each row of the data set to each measurement of that row. Performing mean centering does not change the relative location of each point to each other; it only changes the mean to zero and the centroid location to zero coordinates.

Let the resulting data set after mean centering be represented by $\mathbf{X}$. PCA transforms the data set $\mathbf{X}$ into a new data set $\mathbf{Y}$ with smaller dimensions $(\mathrm{m} \times \mathrm{p})$ which characterizes most of the variances in the original data set. The relationship between the new data set $\mathbf{Y}$ and the data set $\mathbf{X}$ can be expressed using a transformation matrix $\mathbf{T}$ with dimensions $\mathrm{m} \times \mathrm{n}$ as follows

$$\mathrm{Y} = \mathrm{TX} \tag{1}$$

Y is named the score matrix and it combines scores each observation obtains for different factors into a matrix. These factors are called principal components and they are formed in such a way that the first principal component accounts for most of the variances in the original data set, the second principal component for the second most variances in the data set, and so on. The principal components in Y are arranged in descending order, with the first principal component representing the factor(s) producing the greatest variances in the original data set, while the last principal component representing the factor(s) producing the least variances. The score of each observation for each principal component can be thought of as a coordinate along each principal component axis representing the location of each observation along each axis. The first principal component will have the greatest score span whereas the last principal component will have the smallest span. The first principal component is made to have the greatest span by rotating the cloud of data in such a way that the distance of each point of the cloud to the first principal component axis is minimized, while assuring that the axis goes through the zero centroid. It is for this reason that PCA requires mean centering of the original data set prior to application.

In mathematical term, the transformation matrix T in Eq. (1) is called the loading matrix. It contains coefficients which are used to compute the score matrix through linear combinations of the variables in the data set X. The rows of the loading matrix T correspond to the eigenvectors of the covariance matrix of X and they can be obtained by decomposing the matrix X using singular value decomposition and use that decomposition to construct the covariance matrix of X as follows.

$$\frac{1}{\mathrm{p}-1}\mathrm{XX}^{\mathrm{T}} = \mathrm{U}\frac{\Sigma^2}{\mathrm{p}-1}\mathrm{U}^{\mathrm{T}} \tag{2}$$

where U is an orthonormal matrix ($\mathrm{UU}^{\mathrm{T}}=\mathrm{I}$) whose columns represent the eigenvectors of the covariance matrix of X (hence $\mathrm{T}=\mathrm{U}^{\mathrm{T}}$), and Σ is given as

$$\Sigma = \begin{bmatrix} \Sigma_1 & 0 \\ 0 & \Sigma_2 \end{bmatrix} \tag{3}$$

with the diagonal terms being represented by the singular values $\Sigma_1=\mathrm{diag}(\sigma_1, \sigma_2, \ldots, \sigma_m)$ and $\Sigma_2=\mathrm{diag}(\sigma_{m+1}, \sigma_{m+2}, \ldots, \sigma_n)$.

The singular values Σ_1 and Σ_2 in Eq. (3) are arranged in descending order ($\sigma_1 \geq \sigma_2 \geq \ldots \geq \sigma_m \geq \sigma_{m+1} \geq \ldots \geq \sigma_n \rightarrow 0$). Each singular value indicates how much variance its corresponding eigenvector explains in the original data set. Therefore, Σ_1 represents the factors that have the biggest influence on the data set (e.g., the effects of temperature and the effects of damage) while Σ_2 represents the factors with the least effects on the data set (e.g., noise). Since Σ_2 can be very small and close to zero, it is usually discarded to reduce the dimensions of the original data set since these factors do not influence the data set significantly.

By applying Eq. (1), the score matrix Y can be generated. Usually, to reduce the dimensions of the original data set, only the first m rows of the loading matrix T are used to construct the score matrix. However, in this study, all the rows are kept since in this study, PCA is used to extract the similarities and differences in the original data set rather than reducing the dimensions of the data. Analyzing only the first few rows of the score matrix (first few principal components), damage detection can then be performed.

2.2 Visual interpretation

To demonstrate how PCA can be used to extract patterns in a data set composed of damage sensitivity features to distinguish damage from temperature effects, a visualization interpretation is given below. Consider a data set representing marks obtained by four students in eleven tests given in Table 1. The students in this example represent the observations while the tests represent the variables that affect the data set.

Table 1 Test results for the four students

Test №	Student A	Student B	Student C	Student D
1	70	71	71	73
2	65	63	64	65
3	75	77	75	76
4	80	81	79	82
5	79	82	80	80
6	70	70	65	72
7	71	70	64	71
8	80	82	75	80
9	60	61	60	60
10	65	67	70	65
11	85	87	85	86

From the table, it is difficult to determine which students performed similarly and which students differed from the rest. Thus, by applying PCA on the data set, patterns governing the data set can be captured, and important information on how each student compares can be obtained.

Fig. 1 gives the plots of the first and second principal components of the data set in Table 1. From the second principal component plot, no important information on which student is outlier from the rest can be obtained since the scores of all students are well distributed along that axis. However, from the first principal component plot, it can be seen that the scores of students A, B and D cluster together on the right hand side of the plot, while student C is on the left hand side of the plot. This indicates that student C performed differently from the rest of the students. Looking back at the data set given in Table 1, it can be seen that, student C performed better in test 10 than in tests 6 and 7 while students A, B and D performed better in tests 6 and 7 than in test 10. Thus, through PCA, patterns in the data set have been extracted and important information on how each student compares has been obtained. Similar to the example demonstrated here, it is expected that damage effects can be distinguished from temperature effects affecting damage sensitivity features for damage detection.

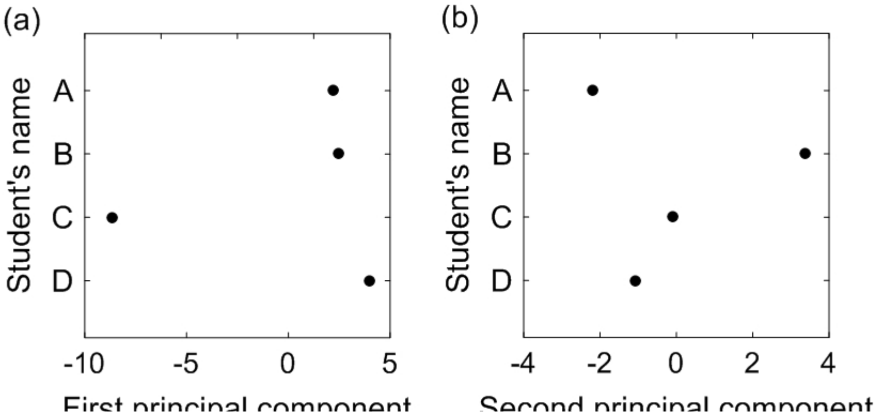

Fig. 1 Graph of: (a) first principal component and (b) second principal component

2.3 Damage detection method

As shown previously, PCA can be used to extract patterns in a data set, and the first principal component will account for the factor(s) creating most of the variances in the data set, the second principal component for the factor(s) creating the second most variances, and so on. Therefore, to enable the first principal component to account for the effects of the changing temperature conditions, damage sensitivity features obtained from two extreme and opposite temperature conditions (e.g., temperature at -30 °C and 70°C) can be used to enhance the variability caused by the temperature effects in the data set. The axis representing that temperature factor will have the largest span and hence, variances. The two extreme and opposite cases will be at each other's end on the first principal component plot. If damage sensitivity features of the undamaged structure gathered at a normal temperature condition (e.g., temperature at 20 °C) is then added to the two extreme cases data set and PCA be performed, then, that observation will have score in between the two extreme cases. If now, damage sensitivity features obtained from a damaged structure is added to the two extreme cases data set and PCA is applied, that observation will situate outside the two extreme cases and will be at the far end of the extreme cases scores. Hence, by using this approach, damage effects can be distinguished from temperature effects affecting damage sensitivity features.

Therefore, to perform the proposed damage detection method, a baseline of the undamaged structure consisting of damage sensitivity features obtained at two extreme and opposite temperature conditions needs to be created. Then, subsequent measurements can be added to the baseline one at a time to create different data sets, and PCA can then be applied on each data set for data processing. Analyzing the first few principal components of the score matrix, damage effects can then be distinguished from temperature effects. The undamaged structure will lie in between the two extreme cases while the damaged structure will lie outside the extreme cases in the principal component plot.

The number of principal components to analyze for damage detection needs to be chosen carefully to avoid false alerts. As a general rule, the principal components that have the baseline scores obtained from the two extreme cases to have a separation between them should be analyzed for damage detection. The principal component in which the two baseline cases are mixed together, should be discarded as well as the succeeding components. The reason behind this is that in the creation of the baseline, two extreme and opposite cases have been selected on purpose so that they have a separation between them to indicate two different behaviors obtained by the effects of the same factor(s).

A description of the procedures to follow to implement the proposed method for damage detection is given in Fig. 2. It should be noted that procedures 3 to 6 should be repeated so that new measurements can be analyzed for near-real time monitoring.

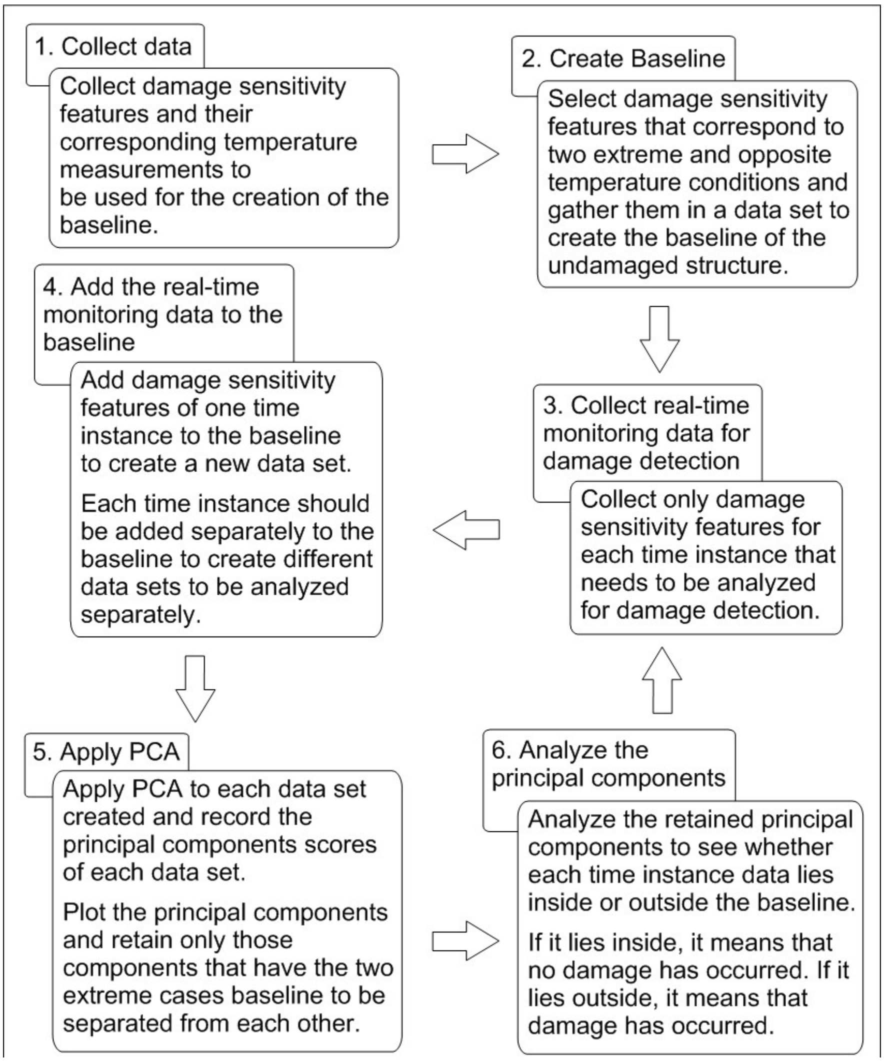

Fig. 2 Procedures to follow for damage detection

3. TRUSS STRUCTURE CASE STUDY

A numerical two-dimensional truss structure model (Fig. 3) subjected to a varying temperature is used in this paper to test the robustness of the proposed method to distinguish damage from temperature effects affecting damage sensitivity features. The truss structure is composed of 31 members and is assumed to be made of steel material with Young's modulus of 200 GPa, density of 7850 kg/m³, and cross-sectional area of 0.001 m². To simulate a varying temperature condition, the Young's modulus of the structure is assumed to be temperature dependent as shown in Fig. 4, with reference temperature taken at 20 °C. The range of temperature considered in this example is -10 °C to 40 °C and the temperature across the whole structure is assumed to be constant. The truss structure is built in MATLAB and the first four natural frequencies of the structure are assumed to be readily available to be used as damage sensitivity features to be analyzed using the proposed method. Damage in the structure is assumed to be represented by a reduction in axial stiffness of the members of the structure.

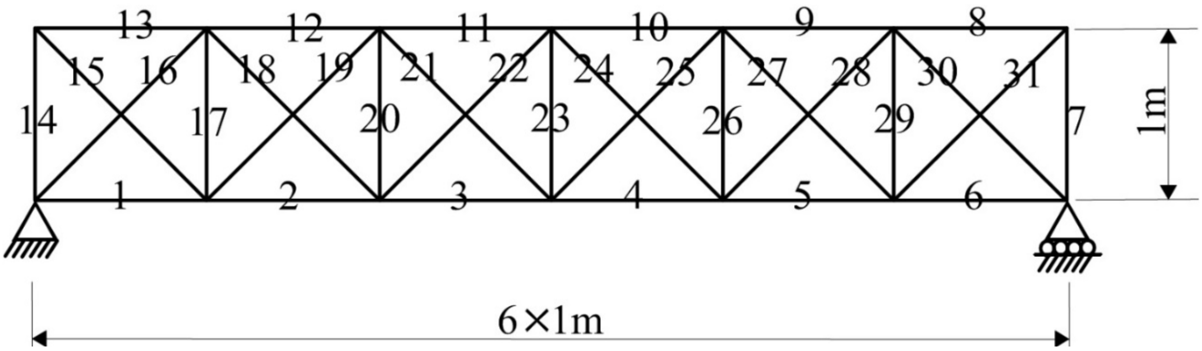

Fig. 3 Two-dimensional truss structure model

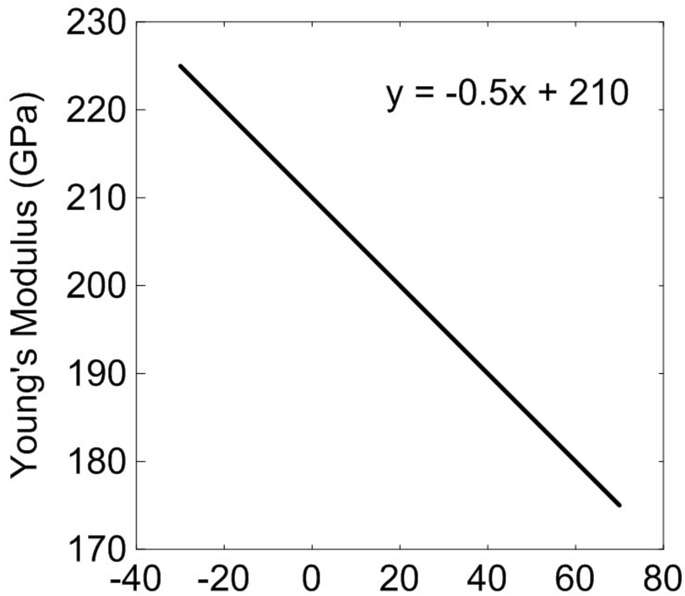

Fig. 4 Graph of Young's modulus versus temperature

The variations of the first four natural frequencies of the truss structure with temperature are given in Fig. 5. From Fig. 5, it can be seen that the natural frequencies decrease with an increase in temperature. Thus, using the natural frequencies as damage sensitivity features for damage detection may lead to false damage alerts if the effects of the changing temperature are not considered. Hence, by applying the proposed method, temperature effects can be distinguished from damage effects on the affected natural frequencies of the structure.

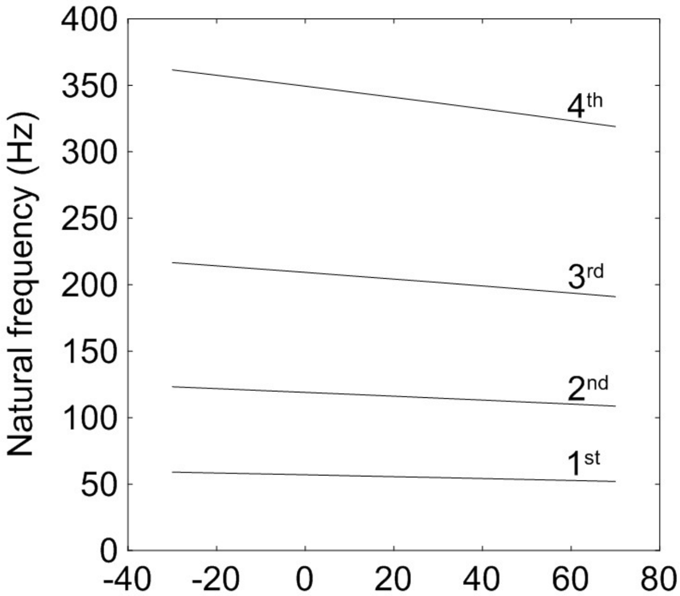

Fig. 5 Variations of natural frequencies with temperature

Three undamaged cases and three damaged cases ranging from single damage to multiple damages subjected to a varying temperature are used to test the applicability of the proposed method for damage detection under changing temperature conditions. Descriptions of the cases are presented in Table 2. To further illustrate the cases, for example, the truss structure in the undamaged case 1 is assumed to be at a temperature of -10 °C, while in the damaged case 1, it is assumed to be at 10 °C with element 20 having a damage extent of 5 %.

Table 2 Description of undamaged and damaged cases

Case number	Temperature (°C)	Element #	Damage extent (%)
Undamaged 1	-10		
Undamaged 2	20		
Undamaged 3	40		
Damaged 1	10	20	5
Damaged 2	10	20	10
Damaged 3	30	5, 8, 10, 15 & 21	5, 5, 5, 5 & 5

4. RESULTS AND DISCUSSIONS

To perform the proposed method, a baseline consisting of damage sensitivity features obtained at two extreme and opposite temperature conditions should first be established. For a better performance of the proposed method, the baseline is made to consist of ten extreme cases with five cases taken at temperatures of -26 °C to -30 °C and five cases at 66 °C to 70 °C with 1 °C interval. Five cases at low temperature and five cases at high temperature are chosen so that the relationship between the natural frequencies and the low/high temperatures can be extracted. To allow the method to perform near-real time monitoring, each measurement to be monitored should be added to the baseline one at a time to form new data sets, and PCA be applied on each new data set for data processing. The resulting new data set will be a matrix of dimensions 4 × 11, with 4 corresponding to the 4 natural frequencies used as damage sensitivity features and 11 to the 10 baseline observations plus the new observation that needs to be analyzed.

As temperature is the only environmental parameter affecting the natural frequencies of the structure considered in this example, and two extreme and opposite temperature conditions have been considered, hence, the first principal component which accounts for most of the variances in the data set will account for the temperature effects. This is because the first principal component has been set to account for the temperature effects by choosing two extreme and opposite temperature conditions which will be at each other's end on the principal component axis. The following principal components which account for the rest of the variances will account for the other factors of the likes of damage affecting the data set. The only case where the temperature effects will not be represented by the first principal component will be when damage in the structure is large enough to create a larger variance in the data set when compared to the temperature effects.

4.1 Undamaged cases

The results of the undamaged cases are first given in Fig. 6. Only the plots of the first and second principal components are given in Fig. 6. Since only the first principal component has the two extreme cases used as baseline to be separated from each other, therefore only that component is analyzed for all the undamaged cases. The first ten observations (dots) in the plots represent the baseline, while the eleventh observation (cross) represents the observation that needs to be analyzed.

From the first principal component plots, it can be seen that all the monitored cases lie between the two extreme and opposite cases used as baseline. This indicates that no damage occur in the structure for all three undamaged cases. Only the temperature variation affects the natural frequencies of the truss structure. The evolution of temperature from low temperature to high temperature is also obvious and clear in the plots. The monitored observation moves gradually from the right hand side (low temperature) to the left hand side (high temperature) with increasing temperature, as shown from Fig. 6(a) to Fig. 6(c). Thus, it may be concluded that, as well as distinguishing temperature effects from damage effects affecting the natural frequencies of the structure, the method can also give a rough indication of the temperature condition the structure is faced to.

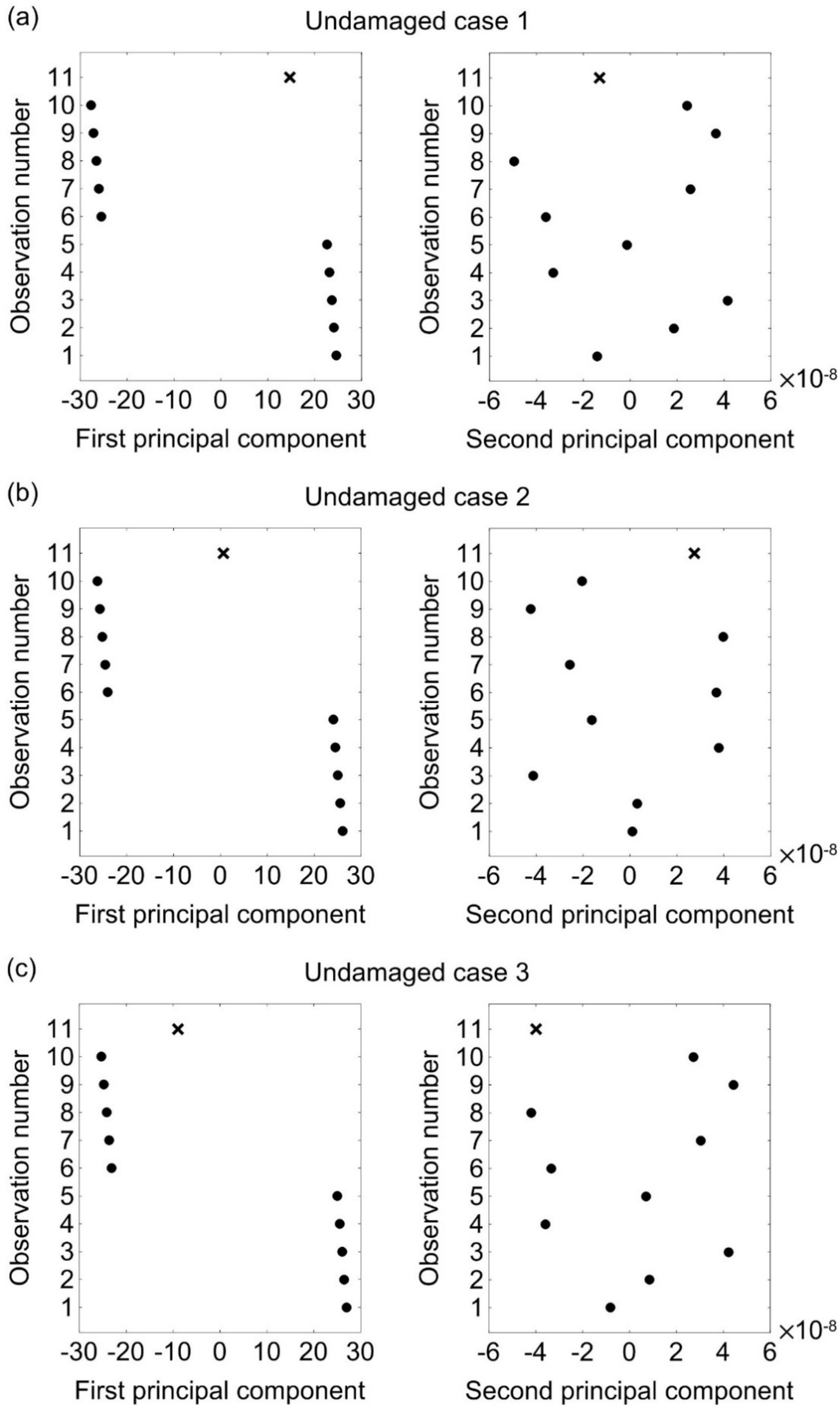

Fig. 6 Graphs of first and second principal components for undamaged (a) case 1, (b) case 2 and (c) case 3

4.2 Damaged cases

4.2.1 Damaged cases 1 and 2 Since damaged cases 1 and 2 have the same temperature condition and same damaged element but with different damage extent, the results for these two cases are given here in Fig. 7 and Fig. 8, respectively for comparison. Note that only the first two principal components are given and analyzed for both cases since only these two components have the low and high temperature baselines to be separated from each other.

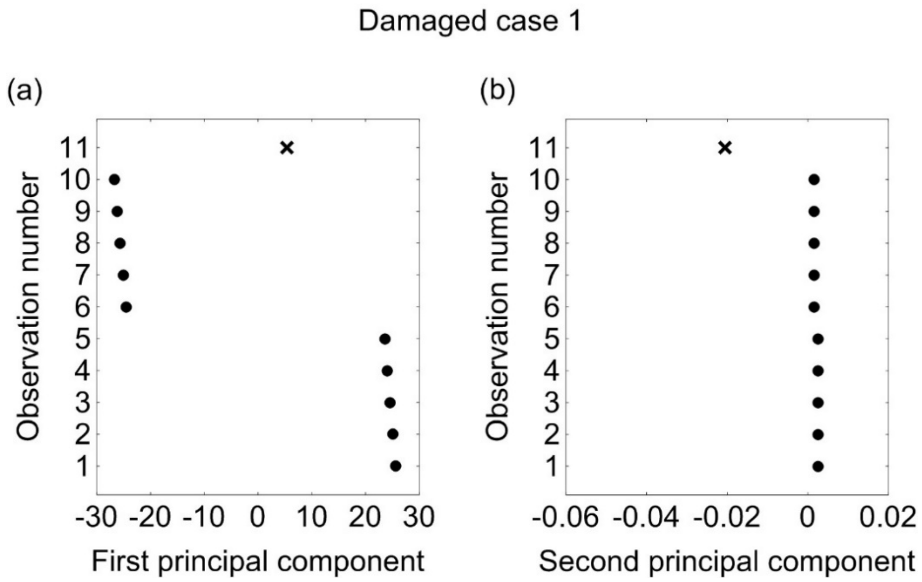

Fig. 7 Graph of (a) first principal component and (b) second principal component of damaged case 1

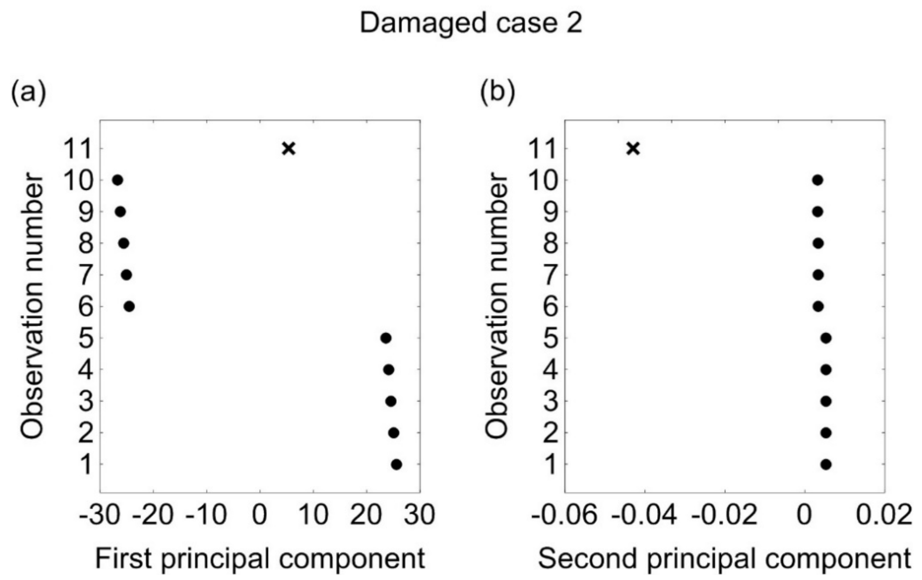

Fig. 8 Graph of (a) first principal component and (b) second principal component of damaged case 2

In the first principal component plot of both cases (Fig. 7(a) and Fig. 8(a)), the monitored cases lie between the two extreme cases. This indicates that the temperature the structure is faced to in both cases, lies somewhere between -30 °C and 70 °C. Moreover it can be seen that the score value for both cases are relatively close. Thus, it may be concluded that the temperature condition both cases are faced to are similar.

In the second principal component plots (Fig. 7(b) and Fig. 8(b)), both monitored cases lie outside the baseline. For both cases, the two extreme cases used as baseline cluster together on the right hand side of the plots with a separation between them observed, while the monitored cases are at the opposite end (i.e. on the left hand side of the plots). This, therefore indicates that the second principal component represents another factor(s) of the likes of undamaged and damaged effects affecting the natural frequencies of the truss structure. Hence, damage alert is raised for both cases. It can also be seen that the score value of the monitored cases differ in this second principal component. The monitored case score value for damaged case 1 has a smaller deviation from the baseline than that of damaged case 2. Since this principal component represents the undamaged and damaged effects affecting the natural frequencies of the structure, it can be concluded that the damaged extent for damage case 1 (5 %) is smaller than that of damage case 2 (10 %), which is true. Thus, in addition of distinguishing damage effects from temperature effects, this method can also show the evolution of the damage extent the structure is faced to. Therefore, the method is deemed useful for near-real time monitoring to give the progression of damage in structures.

4.2.2 Damaged case 3 The results for damaged case 3, which is a multiple damages case, are given in Fig. 9. Similar to the previous damaged cases, only the first two principal components are analyzed since only in these two components that the low and high baseline observations are not mixed together.

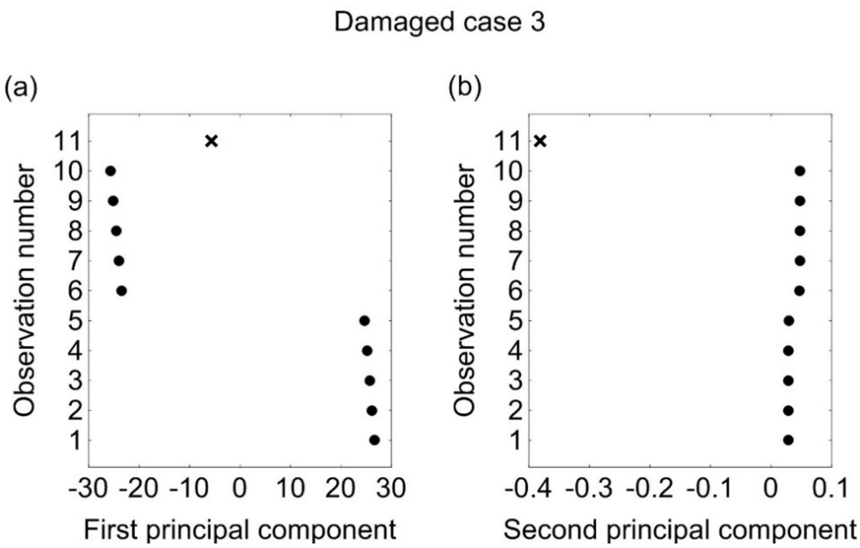

Fig. 9 Graph of (a) first principal component and (b) second principal component of damaged case 3

From the results obtained, similar to the previous damaged cases, the first principal component represents the temperature effects since the monitored case lies between the two extreme cases, while the second principal component represents the undamaged and damaged effects since the monitored case lies outside the baseline. Damage is indicated to have occurred in the structure through the analysis of the second principal component. Thus, for this multiple damaged case, the method performs well in distinguishing damaged effects from temperature effects. It should also be noted that, for all the damaged cases, similar to the undamaged cases, a rough indication of the temperature condition the structure is faced to, can be obtained.

5. CONCLUSIONS

A damage detection method is developed in this paper to analyze civil structures subjected to varying temperature conditions. A novel approach is proposed to create the baseline of the undamaged structure using damage sensitivity features obtained at two extreme and opposite temperature conditions. To allow near-real time monitoring, it is proposed to add the measurements that need to be monitored one at a time to the baseline to create different data sets, and to process each data set using Principal Component Analysis. Analyzing only the first few principal components, damage effects can then be distinguished from temperature effects. The method is tested on a truss structure subjected to a varying temperature to simulate a varying environmental condition. The results demonstrate the ability of the proposed method to distinguish damage effects from temperature effects. The results obtained from the damaged cases also show that the method can give the evolution of the damage extent. The use of the novel baseline proves useful in giving a rough indication of the temperature condition the structure is faced to, without directly recording the temperature measurement. Using only the damage sensitivity features for damage detection and not requiring the temperature measurements after the baseline has been formulated, decrease the risk of failure of the SHM system. Moreover, analyzing one measurement at a time allows the method to perform near-real time monitoring of structures.

However, the method has the limitation that the baseline needs to be constructed from two extreme and opposite temperature conditions which can sometimes be difficult to achieve. Further work is on course to address this limitation.

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