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DATA ANALYSIS APPROACHES FOR STRUCTURAL HEALTH MONITORING

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ABSTRACT

Change or damage detection is an important component for Structural Health Monitoring (SHM) applications. In this paper, the efficiency of two non-parametric damage detection algorithms for bridge monitoring application will be explored and demonstrated on a real life bridge. These algorithms will be based on cross correlation analysis and moving principal component analysis (MPCA) as two statistics-based damage detection algorithms, which do not require a mathematical model for implementation. These methods are termed as data-driven or non-parametric methods, which are quite effective for practical use in real life as long as the limitations are understood and the uncertainties can be evaluated. These methods will be demonstrated on a real life bridge, which was subjected to some damage scenarios that are critical for bridge owners. The effectiveness of these techniques is shown using the real-life data from this unique structure.

KEYWORDS

SHM, monitoring, data analysis, non-parametric, data-driven, model-free, PCA, correlation, movable bridge

INTRODUCTION

There is a growing interest in Structural Health Monitoring (SHM) as an area focusing on condition assessment of different types of structures such as bridges, buildings, towers etc. SHM systems are expected to provide indicators for tracking the health of a structure by combining different sensing technologies and data analysis techniques. With SHM technologies becoming more available and affordable with the recent developments in sensing and computing technologies, additional challenges regarding analysis and management of the acquired data also increase. Over the last 20 years, the aging transportation network has gained the interest of civil engineering community for bridge health monitoring due to the critic nature of these structures. A variety of studies for bridge health monitoring can be found in literature from different perspectives such as damage/change detection, reliability, maintenance-cost, structural identification. Especially these publications increase since 1990s to date (Brownjohn et al. 1995; Aktan et al. 1996, 2000; Enright and Frangopol 1999; Fujino 2002; Catbas et al. 2007). Very recently, a comprehensive document was published by the ASCE Structural Identification Technical Committee to discuss several concepts related to structural health monitoring (Catbas et al, 2013, Catbas, and Kijewski-Correa, 2013).

The first step for developing an SHM system is the implementation of the sensors and data acquisition systems. The next step is establishing the data collection and data analysis methodologies to assess the condition of the structure. The data analysis methodologies can be utilized for different objectives such as visual checks, statistical analysis, traffic characterization, environmental effect characterization and damage identification. After the data collection and analysis step, the last step for the SHM system is the decision making for a number of purposes. These steps can help the infrastructure owners by indicating the worsening conditions such as graduate deterioration or instantaneous damage. This information, which is generated with the help of SHM system can also be used by the owners in scheduling repairs or preventive maintenance to maximize the service life of the structure. Moreover, the root causes of the problems can be identified and future designs can be improved using the information generated using the monitoring system.

In terms of data analysis, there are basically two distinct approaches toward an interpretation of SHM data so-called parametric and non- parametric methods (Worden 1997). The parametric approach is preferred in the cases that conceptualization and prediction are of the main concerns (Laory 2011). Alternatively, non-parametric approaches (also called data-driven or model-free) are superior in the circumstances in which creating a behavioural model is either time consuming or expensive, and this aspect is considered as the leading advantage of nonparametric methods over parametric ones (Omenzetter et al. 2004, Catbas et al. 2012). Indeed, model-free approaches are free of geometrical and material information. Also, interpreting a finite element model is not needed for these methods. Unlike parametric approaches, through the nonparametric techniques, a statistical model is generated based on the signal itself, and any change can be detected explicitly by only continuously evaluating this model. Dealing with this statistical model is much more convenient and in most of the cases is preferred to a complex mechanical model. In this paper, the focus will be to present the two main approaches for data analysis of SHM data along with some examples from the author's studies from a real life bridge in Florida.

MONITORING SYSTEM AT A MOVABLE BRIDGE IN FLORIDA

General Characteristics of the Bridge and the Monitoring System

In order to effectively investigate the efficiency of different hardware and software technologies for long-term monitoring of movable bridges mainly for maintenance needs, a representative movable bridge in Florida is instrumented comprehensively with various types of sensors. The data is collected continuously from baseline and also during some critical and common damage conditions that were induced short time in collaboration with the bridge owners. In fact, having access to the data from damage condition is one the unique aspect of this study since there are only a few cases that damage data from a real-life structure is available. The selected movable span of the bridge is the West-bound span of two parallel spans on SR-838, crossing a canal in Ft. Lauderdale, FL. This span was constructed in 1989. It has double bascule leaves, with a total length of 35.7 m, and a width of 16.3 m, carrying three traffic lanes (Figure 1). The most critical electrical, mechanical and structural components are monitored by a comprehensively designed monitoring system consists of an array of 160 sensors, which add up to 200+ channels (Catbas et al.2010). The structure is equipped with appropriate sensors at the most critical locations including, girders, floor beams, stringers, live load shoes (LLSs) and span locks (SPs). In this study, the strain data that are collected by dynamic SGs (Hitec weldable) at 12 individual locations along the bottom flange of the main girders is used. The data are captured with 250 Hz sampling frequency. Figure 2 illustrates the locations of SGs and corresponding nomenclatures, WN refers to West North and ES refers to East South. Field tests were conducted to establish thresholds for conditions that are critical for the maintenance and operation of the bridge. These conditions will be referred as "damage". In collaboration with FDOT engineers, some of the most common structural maintenance problems are identified and subsequently implemented on the movable bridge to simulate the damage condition. One of the most common structural maintenance problems is identified as LLS shim (Live Load Shim) removal.

Figure 1. The real life movable bridge, which has a comprehensive monitoring system (courtesy of Google)

Figure 2. Instrumentation plan for the high-speed strain measurements on structural components

Preliminary Analysis of the Monitoring Data

The bridge that is described above has number of different sensors for structural, mechanical and electrical components. In this section, the focus will be mainly strain measurements to detect commonly observed problems at movable bridges. Visual check of the raw strain data can be considered as the first step to detect non-working and malfunctioning strain gages. This process consists of viewing a graphical representation of real-time or archived data from a sensor channel and inferring from the predicted behaviour of that sensor, whether or not that sensor channel is working properly. A common issue with the strain gage is the sensor drift, which can be defined as general trend of the data to shift to higher or lower readings during the collection. It is important to note that the condition of a sensor is not a constant. For example, a once working sensor may become a non-working sensor if it encounters some sort of trauma. For this reason, visual checking of the raw strain data is a continuous process for data quality control. It should be noted here that visual check of the whole data may not be feasible in case of an automated SHM system and the above mentioned procedures for checking the data should be automated for such applications.

Traffic Induced Strain Data

Extracting statistical information, such as maximum, minimum, mean, standard deviation, correlation and root mean square can be considered as another type of data analysis approach, which helps the engineer, not only to understand the data behavior, but also to interpret the data. In addition to these advantages, statistics also help for identification of traffic behavior by identifying the truck induced stress levels, ADTT numbers etc. Figure 3 shows the daily maximum and minimum strains coming from the bottom flange of the East South stringer from the period of October 15 to January 15. Since the stringers are the starting point of the load distribution and have smaller cross-sections, higher strain values at stringers are observed compared to some of the other components such as floor beams and main girders. Higher strain values were observed mainly during the rush hour times of each day. Extreme value distribution can also be obtained using the statistical information about the strain. A three months strain data histogram coming from East South stringer is shown in Figure 4 that can be utilized for system reliability estimation and fatigue analysis (Gul et al, 2011).

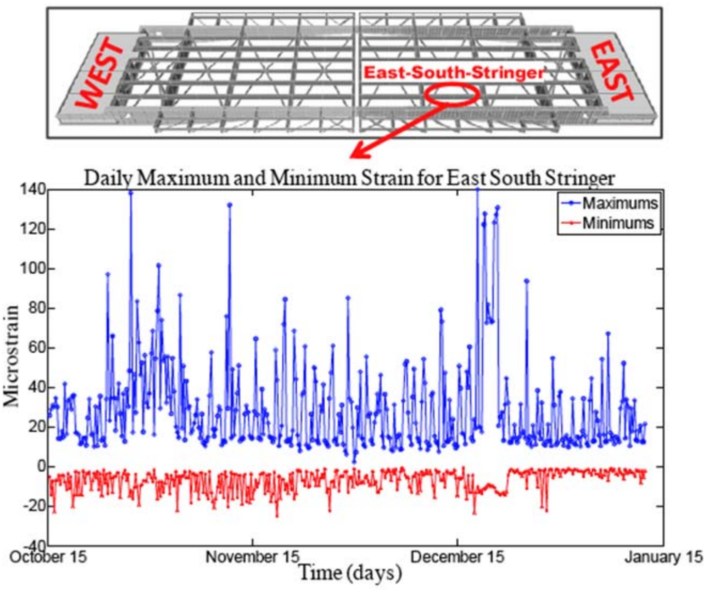

Figure 3. Daily maxima and minima strain for each day from East South stringer

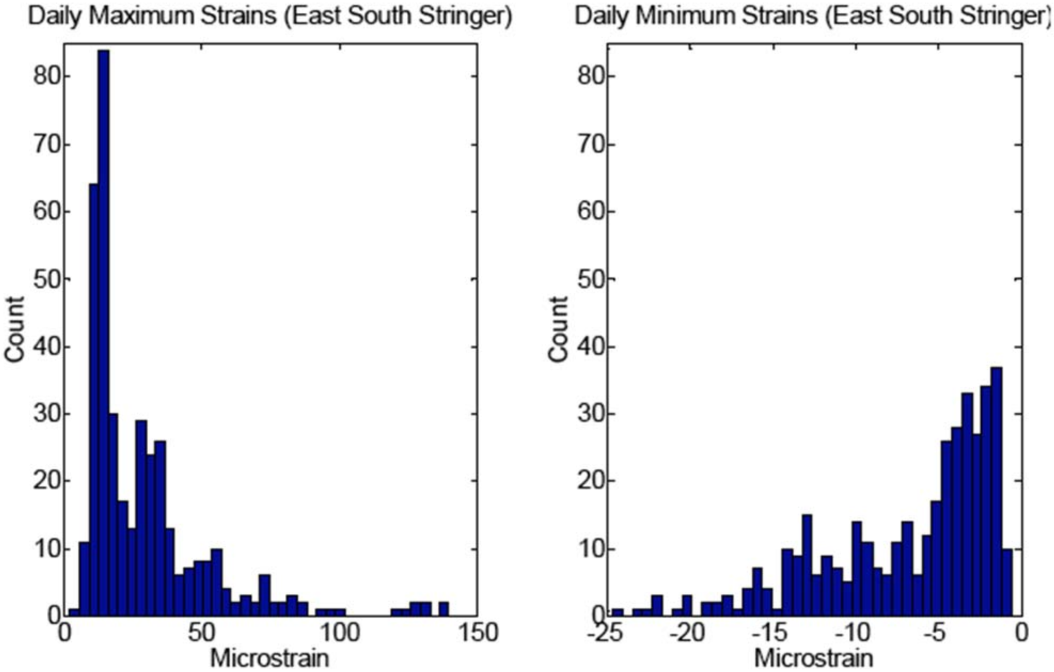

Figure 4. Three months strain data histogram from East South stringer

SOME POSSIBLE DATA ANALYSIS TECHNIQUES FOR SHM

Cross Correlation

After collecting the basic statistical information from each sensor channel for each data set, more advanced data analysis methods can be used for structural damage identification. As indicated in the previous sections, non-parametric or data-driven techniques based on statistical analysis of the data provide certain advantages. In this part of the study, strain correlation based damage identification is presented. Cross correlation, which is a measure of similarity of two data sets in vector form giving a value between +1 and -1. Having similar behavior in data sets gives higher correlation while low correlation indicates either low or no correlated response. General cross correlation coefficient formula is as follows:

$$\rho_{X,Y} = \frac{\sum_{i=1}^{n}(x_i - \bar{X}) \cdot (y_i - \bar{Y})}{(n-1) \cdot \sigma_X \cdot \sigma_Y} \tag{1}$$

where $\bar{X}$ and $\bar{Y}$ are means and σ_X and σ_Y are the standard deviations of each vector. Ideally, the strain channels should have a correlation with the neighbor, or symmetric locations, and the outcome of this correlation will show consistency in the strain levels. In the light of this information, the authors decided to investigate the possible change in the correlation coefficients due to structural changes on the movable bridge (Catbas et al, 2012).

Principle Component Analysis

Two main concerns, delay in abnormality detection along with computational time, inspired the re-vision of classical PCA to make it more practical for long term SHM. Real life employment of SHM involves dealing with large amount of multivariate data. Only a small portion of abnormal data, in comparison to overall data, is available at the time when damage occurs. By means of PCA, the damage will be detectable only when the principal components (eigenvectors) are influenced by abnormal behavior. Subsequently, eigenvectors are subjected to change only if certain amount of abnormal data captured and possibly affected the overall structure of data. This feature makes PCA less effective for long term SHM implementation. Moving principal component analysis (MPCA) was proposed to address this challenge (Posenato et al. 2008). Basically, MPCA computes the PCA within moving windows with a constant size (Malekzadeh and Catbas, 2013).

A sensitive damage index is selected based on PCA outputs. The damage index "(D_{si})" chosen for this study is square root of the sum of the squares of the first two principal components as shown in Eqn. (2)

$$D_{Si} = \sqrt{(PC_1)_i^2 + (PC_2)_i^2} \quad (2)$$

where "$(PC_1)_I$" and "$(PC_2)_I$" are the first and the second principal components of sensor "i" respectively. The reason to just incorporate the first two principal components in the damage index is that the most useful information in the data is covered by the first few principal components values. In fact, the first principal component corresponds to the direction of in which the projected data has the most variance while the second one is perpendicular to the first component. In other words, since more than 95% of the variance (calculated based on the preliminary study) is covered by the first two principal components, these two components are only incorporated in the damage index. It should be mentioned that the number of principal components that should be considered depends on the data and there is not any prescription for all cases. However, in the most cases, the most variance is covered by the first two or three components. Therefore, if any damage occurred in structure, then it should affect the data and consequently variance of data and should be detected by this damage index.

DAMAGE IDENTIFICATION USING DATA DRIVEN METHODS

Damage Cases at the Real Life Bridge

In collaboration with the bridge owner, the author and his students made arrangements to induce a "damage" that is commonly observed at the bridge. This damage is at the Live Load Shoes (LLS), which are the support locations of the main girders when the bridge is in closed position (Figure 5). If misaligned or improperly balanced, the bridge may not fully sit on the LLS. In that case, the dead load and traffic load are transferred to the gears and shafts, which cause damage to mechanical assemblies. Small gaps also lead the girders to pound on the live load shoes, which results in further misalignment, additional stresses, fatigue damage, and excessive wear. For this study, LLS shim removal (Figure 5) is chosen as a damage scenario based on the inspection reports of bascule type of movable bridges in Florida. The West South LLS (WS3) shims which are removed to see the effect of a gap around 3.2 mm up to 4.8 mm.

Damage Identification Results from Correlation Analysis and Principle Component Analysis

Correlation coefficients of the strain channels are tracked for a 25 different data sets before, during and after damage from a three weeks period. First, 10 data sets are collected in 10 days to illustrate the before damage correlation coefficients. Then, five data sets are collected for LLS shims removal case on same day due to time consideration to illustrate the during damage correlation coefficient. Finally, 10 more data sets were collected in a 10 day period to see if the correlation coefficients are becoming their original level.

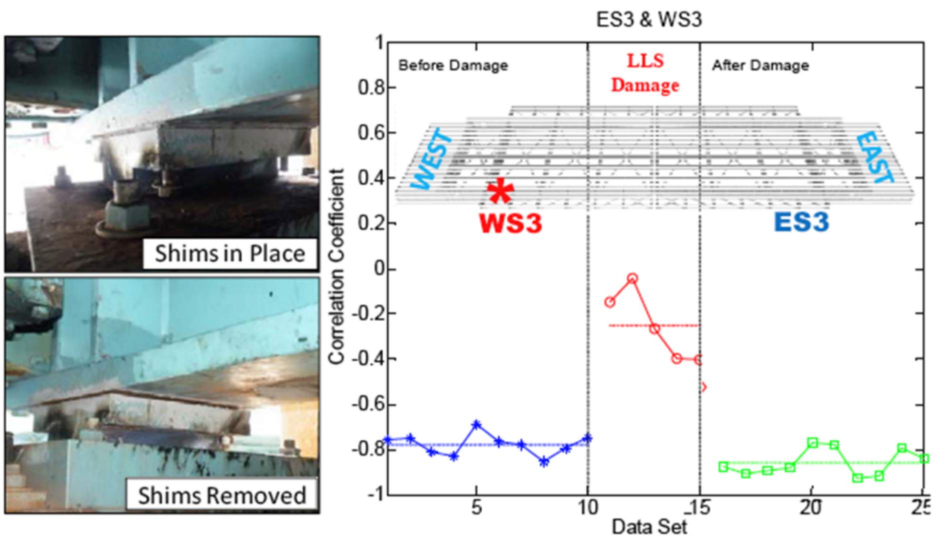

Figure 5. LLS shims and correlation coefficient change before, during, after damage

The correlation coefficient change between the ES3 and WS3 strain gages during the three weeks period are shown in Figure 8. It can be easily seen that the correlation coefficients before damage case are around -0.8, during LLS damage are around -0.3and after damage these coefficients came back to the -0.8 level again but this time with a smaller standard deviation. The reason behind this is the significant effect of the maintenance. The trends of the correlation coefficients are also tracked for different strain gages but they are not presented here for the sake of brevity. More data and results are reported in another publication, which is dedicated to this approach and results (Catbas et al, 2012).

As described before, Principle Component Analysis (PCA) is also investigated for the analysis of the same damage scenario. As it is observed from Figure 6, the PCA values from the sensor WS3 that is positioned close to the location of induced damage is significantly affected by while the one for the sensor EN3 that is installed on the east span (far away from the damage location) does not show any abnormal behavior. Therefore, the results show that MPCA algorithm is effective enough for detecting abnormal behavior out of the data that are even influenced by noise and outliers.

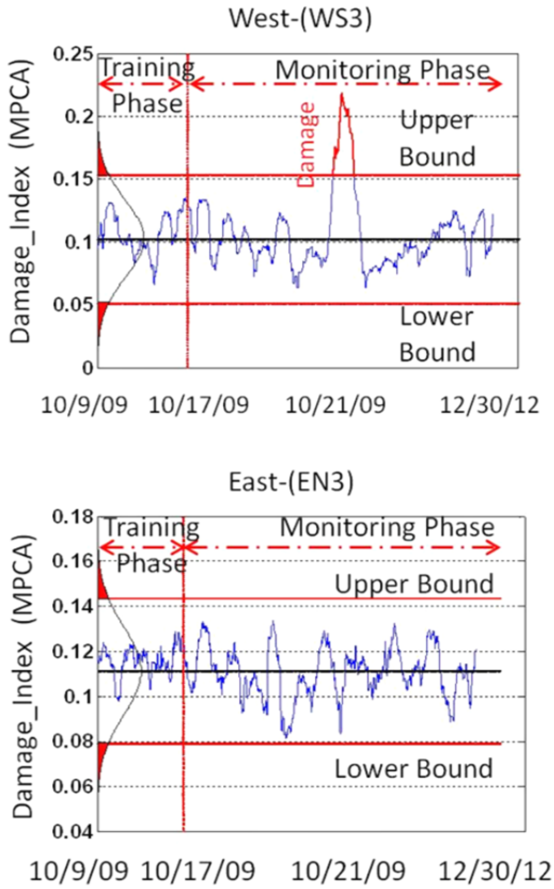

Figure 6. Moving Principle Component Analysis (MPCA) results related to a sensor close to damage location (WS3) and a sensor far from damage location (EN3)

CONCLUSIONS

In this paper, a critical aspect of SHM, data analysis approaches, is discussed. There are different data analysis approaches to extract meaningful information from SHM data. Non-parametric, model-free or data-driven methods for the analysis of SHM data provide certain advantages such as being fast, less requirements for interpretation and data reduction from large sets to few features. It is clear that some level of raw data analysis is necessary for issues such as large magnitudes of responses, functionality of the sensors, and to evaluate data quality whereas statistical analysis-based non-parametric approach is a fundamental step for advanced analysis methodologies. In this study, strain measurements from a real bridge are presented. A movable bridge in Florida was subjected to short term maintenance problems (“damage”) in order to investigate damage identification methods.

First, it is shown that strain data analysis by means of correlation based damage identification methodology is an effective way of handling large amount of data while detecting damage. Based on the results, it is seen that this new methodology can help to track and detect any permanent change by means of strain measurements under any traffic loading. In the second part of this study, the strain data that are collected from the same bridge is used to test the efficiency of moving principle component analysis (MPCA) method. The MPCA algorithm detected the damage. This method used single channel data to detect the damage. It is important that there should be sensors somewhat near the critical locations. Therefore, considering both correlation and MPCA analysis on the real-life study, promising results are obtained. It should be indicated that that there could be a suite of techniques and features to be available for implementation in SHM systems since one particular technique/feature may not be very reliable or sufficient for a particular case and/or structure.

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