Structural Health Monitoring using Statistical Tools

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2. Abstract

One of the major obstacles in structural health monitoring tends to be physical limitations. Visually assessing damage might not always be possible, and as such alternative methods such as statistical methods are much more convenient than traditional methods. By using statistical process control, damage can be detected in structures. More precisely, by modelling a known intact structure and finding an autoregressive model (AR) for it, statistics are used to look for trends between intact and damaged structures. In order to quantify a difference statistically, control charts are used to observe the difference in means between the AR coefficients of the intact and the damaged structure. The AR coefficients were chosen by a process of convergence in reducing autocorrelation within the recorded data. A damaged structure will show in a control chart as an out of control process, with a substantially different sample mean as well as a different standard deviation.

3. Introduction

Detecting damage within structures has traditionally been limited to superficial methods such as visually locating damage or non-destructive testing where routine inspections can be done. However, a great deal of damage is difficult to detect by traditional methods, due to the difficulty of locating visible damage and locating it before failure occurs in the structure. Structural health monitoring (SHM) revolves around different techniques in damage detection. Ng and Chan (2014) explain that SHM is a process for monitoring health and determining the performance of the structure. This allows more precise damage detection methods to be carried out without the risk of wasting time on a structure that is not actually damaged. It is a constantly evolving field with new methods still being discovered.

In terms of structural health monitoring, damage is defined by Sohn et al. (2004) as a change in a structure that adversely affects a structure. Typically structural health monitoring is done by studying the frequencies in response to an excitation. Excitations are typically two types: ambient and forced. An ambient excitation according to Chintalapudi (2006) is caused by natural phenomena such as wind or regular human activity. Any artificial method causing excitation in a building is considered as a forced excitation. The structure used in this report for example was excited by a controlled shaker.

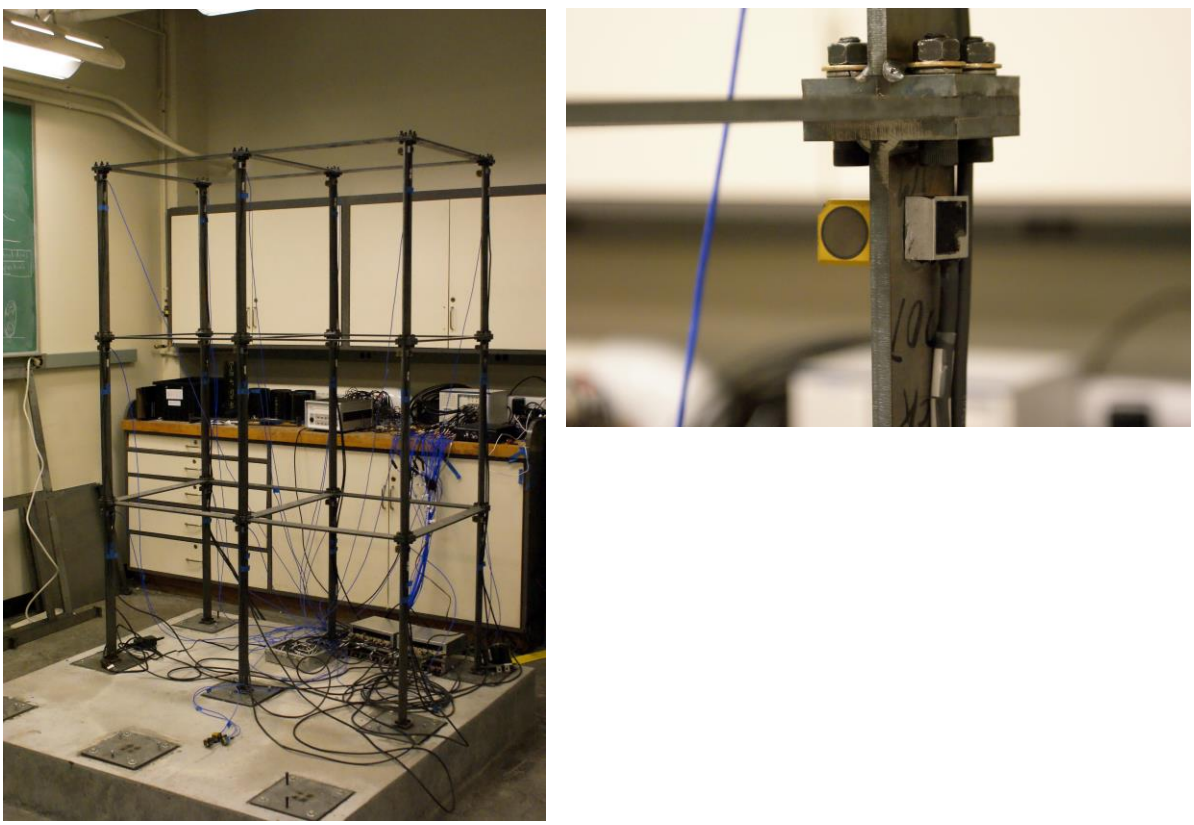
Control charts are a statistical tool used to identify variability within processes as defined by Montgommery (2009). By using the standard deviation and means of samples, a plot is drawn to show how much a sample deviates from the process mean. By comparing the mean of a subgroup to the overall mean of the process, a trend can be detected within the process. This is useful because even if the output is within the accepted range, a trend might be an early warning sign for a future problem.

In this project, data from a structure that was excited with a white Gaussian noise is used to construct control charts to detect damages to the structure as outlined by Sohn and Farrar (2000). A Principle Component Analysis (PCA) is performed to compress the data from 3 axes in 18 sensors (resulting in 54 channels of data) to one principle component. From that, the principal component is projected to an Auto Regressive (AR) model of the time series to determine the coefficients of the model. These coefficients are used to construct the control chart. The coefficients were chosen as the metric since they best described the parameters of the original time series data. Once a control chart for the undamaged structure is constructed, the coefficients of the damaged structure are superimposed onto the baseline metrics (centre line, upper and lower control limits) obtained from the undamaged control chart.

4. Methodology

4.1. Experimental Setup

The initial acceleration data used in the algorithm is collected from a two bay three story structure. It is a hollow structure connected by steel beams attached together using bolts. The dimensions of the columns of the structure are 60cm x 5.08cm x 0.64 cm, with a total structure dimension of 1.8m x 0.6 m x 1.2m. To vibrate the structure, a shaker is used that can output different types of frequencies. Different damage scenarios are created by loosening bolts at different locations. Accelerometers are attached evenly across the structure that can record the structures movement in the



Experimental structure and close up of sensors and bolts used.

x, y, and z axes. There are 18 sensors attached overall. The structure is shaken for 30 seconds and the sensors record at a sampling rate of 6000 Hz resulting in 180,000 data points per axis per sensor. There are five different damage scenarios that are tested in this experiment:

1. Loosening 2 bolts around sensor 17 – which is close to the shaker

2. Loosening 4 bolts around sensor 17
3. Loosening 2 bolts around sensor 1 – which is furthers from the shaker
4. Loosening 4 bolts around sensor 1
5. Loosening 2 bolts at both sensor 17 and sensor 1 simultaneously

4.2. Data Analysis

The acceleration data from the undamaged and damaged tests is then imported into MATLAB to begin analysis. Firstly, a principle component analysis (PCA) is done on the data. This is done to combine the information from each of the three axes of the 54 channels of data into one time series. After the PCA, the acceleration data from an individual test is divided into three groups which become the observational samples in the control chart for each test. This is done to have a suitable sample number for each observation (test) in the control charts. The observational mean for each test is represented as a point on the chart.

An autoregressive model

$$y[k] = \sum_{i=1}^{N} a_i \, y[k-i] + u[k]$$

is then estimated by MATLAB using the Yule-Walker method on each of the three time series. Above is an example of an AR model of order N where y is the measurement variable, k is the time index, and $y[k-1]$ ... $y[k-n]$ are past measurements; $u[k]$ is the applied input. The autoregressive model (AR) is computed to remove the autocorrelation in the time series data such as drifts, etc.

After the AR model is computed, the coefficients of the model generated are extracted and organized by experimental test configuration. We rely on the use of control charts. A control chart is only relevant for a particular a_i, where i is a fixed value from 1 to N. For these control charts, the observations axis (x-axis) is for the experimental tests, and the samples axis (y-axis) is for some average we will define later for the particular a_i. See Figure 1 for an example.

A control chart has a centre line, an upper control limit (UCL) and a lower control limit (LCL). For the relevant a_i and for a particular test, the average ($\bar{a}_i$) and standard deviation (σ) is calculated across the three data groups of that test. The values $\bar{a}_i$ from all the tests from the particular damage scenario are averaged again to construct the centre line ($\bar{\bar{a}}_i$) of control charts. The lower and upper control limits of control charts are constructed from $\bar{\bar{a}}_i \pm 3\sigma$. In our case the centre line and limits were constructed from measurements done on an intact structure. All other test results are superimposed on these limits and centre line.

For analysis, for a particular control chart, the number of tests for which $\bar{a}_i$ lies outside of the control limits is used to construct a metric to determine the damage level of the structure. This metric is a function of the number of out of control points, as their weighted distances to the centre line.

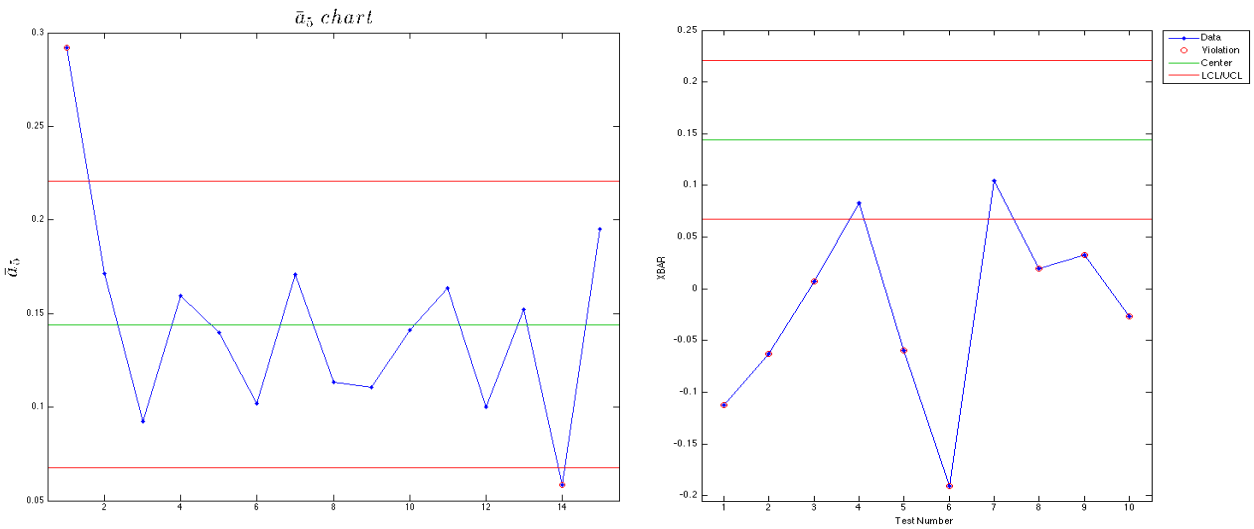


Figure 1. Example of intact Control Chart (Left) and damaged control chart (right)

Figure 1 shows the control chart for a_5 for a 5th order AR model. The chart on the left is the result for the intact structure's acceleration data. The chart on the right is the result for a structure with 4 bolts loosened. As expected, the control chart shows that the points are significantly outside the limits.

This procedure is done for each coefficient of the AR model, *i.e.* a_i. The MATLAB program developed in this study was run for AR orders of 1 to 9. AR model orders were chosen in order to determine which order would be the most useful overall.

5. Data Collection

Acceleration data was collected for two days. On Day 1, experiments were conducted on both the intact structure and the 3 damage scenarios. On Day 2, only the intact structure was experimented on. In Day 1, 15 experimental tests on the intact structure were conducted, while Day 2 had 18 tests conducted. For control chart purposes the data sets were arranged into 5 different ways (baseline sets) as such:

1. All 15 tests from Day 1
2. 15 randomly selected tests from Day 2
3. All 18 tests from Day 2
4. 10 randomly selected tests from each of Day 1 & 2

5. 15 randomly selected tests from Day 2 & all 15 tests of Day 1

For each of these baseline cases, the control charts were constructed for AR orders from 1 to 9.

Other parameters that were modified were the number of principle components being analysed. Initially, the data of 21 channels of data was combined for the PCA since the plot of the covariances showed that 30% of the information was contained in the first principle component alone as shown in Figure 2. Since the data from the other 33 channels did not contribute significant information to the PCA, they were discarded. However, upon running the algorithm, many of the intact structure's control charts contained a high percentage of out of control points. Changing this to 54 channels (as to include all sensors) resulted in much more desirable control charts.

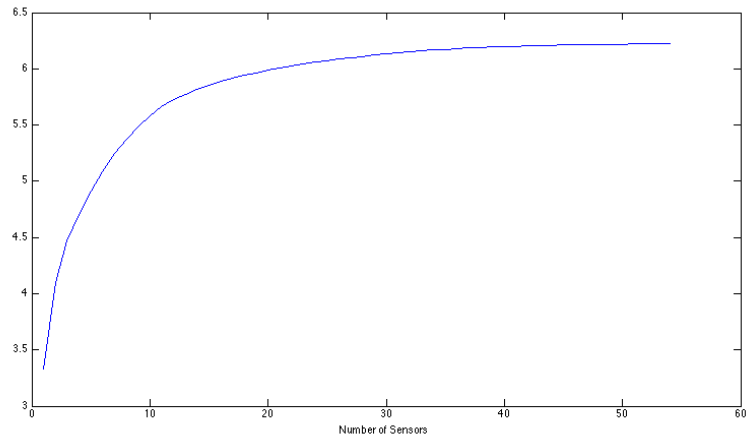


Figure 2. Eigenvalues of Covariance

Another parameter that was modified was the offline downsampling of the raw acceleration data. Initially, the data was down sampled by a factor of 12, changing the sampling rate from 6000 Hz to 500 Hz. The down sampled data resulted in very inconsistent results. Many of the intact structures' control charts ended up with a very high percentage of out of control points; in fact some of the intact structures' control charts had more out of control points than the damaged structures' control charts. Therefore, none of the data was down sampled and the original sampling rate was retained.

6. Results

Out of the 5 baseline cases, the only two useful results came from Case 1 and 3. Interestingly, using 18 tests versus 15 tests of day 2 yielded much different results. In fact, the other three Cases 2, 4, and 5, all resulted in the intact structure's control charts having at least 50% or more out of control points. In addition, the out of control points in the damaged structures were not consistently reflecting the proper damage level.

After deciding that Case 1 and 3 were to be considered in the remaining analysis, to improve our assessment of the damage, the metric has also leveraged the distances of all points to the centre line. Indeed it was found that including the distances in the metric resulted in better detection of damage. In particular, it was found that the damage near sensor 1 (Damage Scenarios 3 & 4), which was the furthest away from the shaker, when distance is considered was easier to detect.

To illustrate the results, the results of a_5 of an order 5 AR model are shown in the following table. The results are for Cases 1 & 3. For these cases, the intact structure did have out of control points, however none of the damaged scenarios had greater out of control points than the intact structure. It is important to note that in the results of Case 3, one damage scenario had equal out of control points to the intact structure's control chart. The scenario in question though is one of the minor damage scenarios.

a_5 Out of Control Points						
	Sensor 17 2 Bolts (Damage Scenario 1)	Sensor 17 4 Bolts (Damage Scenario 2)	Sensor 1 2 bolts (Damage Scenario 3)	Sensor 1 4 Bolts (Damage Scenario 4)	Both sensors (Damage Scenario 5)	Intact
Case 1	3	4	3	8	7	2
Case 3	3	4	4	8	7	3

a_5 Average Distance to Centre Line						
	Sensor 17 2 Bolts (Damage Scenario 1)	Sensor 17 4 Bolts (Damage Scenario 2)	Sensor 1 2 bolts (Damage Scenario 3)	Sensor 1 4 Bolts (Damage Scenario 4)	Both sensors (Damage Scenario 5)	Intact
Case 1	0.05	0.07	0.06	0.12	0.07	0.04
Case 3	0.04	0.07	0.05	0.15	0.07	0.12

Table 1. Results for a_5 of AR order 5

It should be noted that for a particular AR model, not all coefficients will accurately reflect damage. For example, in Day 1, orders 8 and 9 produced results that detected damage in the first, seventh, and ninth coefficients. Within day 2, the charts past the third coefficient on all orders mostly contained charts that had higher damaged out of control points than the intact structure.

7. Conclusion

While the out of control points alone are not enough to definitively detect damage, the distances of the points to the control chart help improve the results. Indeed, a drawback to this method is that the statistics for an undamaged structure should be determined *apriori*. Once available, control charts are a quick method for determining if further investigation and assessment of the structure is required. Further studies can be done on this method to enhance detection of damage. For example, it was found that having a number of baseline cases, number of experimental tests on the intact structure, should be close to the number of tests on the done on the damaged structure.

One additional baseline case to attempt would be 10 tests containing a random mixture of Days 1&2. In addition, collecting data over a longer number of days would also result in more combinations of baseline cases to attempt. With the available data, it was found that using all the data from each day individually gave the most reasonable intact structure data. Unfortunately, it is not clear what choice for the order of the AR model would work best with all cases.

Minor damage might not be easily detected with this method, however major damage, that might still be difficult to detect using traditional methods, can be detected using the method of statistical analysis. Considering the ease and speed of running this program, it can be a quick method for damage detection.

8. Acknowledgement

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