APPLICATION OF DAMAGE DETECTION ALGORITHMS TO BRIDGE FIELD TEST DATA

Anne S. Kiremidjian[1], Allen Cheung[1], Pooya Sarabandi[2] and Krishan Nair[1]

Abstract

Field data from experiments where damage has been introduced systematically to a structure are difficult to find yet essential for validation of damage detection algorithms used in structural health monitoring. Such an experiment was recently conducted by Vibration Consulting Engineers in Vienna, Austria and the data were made available to the authors. In this paper, the results from the analysis of the data are summarized and the efficacy of the damage detection algorithms is assessed. It is found that in most cases the algorithms are able to identify the damage. Good results are obtained when damage is quantified and localization can be explained.

Introduction

Structural health monitoring (SHM) for civil engineering applications is taking advantage of the latest technologies in sensors, wireless networks, and data analysis methods to protect civil infrastructure and preserve life safety. SHM consists of damage diagnosis and residual life prognosis. The goal of damage diagnosis is to detect, localize, and quantify structural damage arising from a variety of sources, including long-term degradation such as corrosion and short-term events such as earthquakes, and then to inform decision-makers about the proper responsive action. Interest in using wireless sensing networks for structural health monitoring has increased as more research demonstrates successful application to increasingly complex structures. Wireless networks are desirable, because they are cheaper and easier to install and maintain than equivalent wired networks. However, they require that the power consumption be minimal thus making it necessary to limit data transmission.

One method of detecting damage in a structure is by measuring the structure's vibration characteristics through strain or acceleration. The premise is that changes to structural properties caused by damage will change the way a structure responds to ambient motions. Recent research has shown that statistical signal processing and pattern recognition techniques can be used to diagnose damage successfully (e.g., Nair et al., 2006, Nair and Kiremidjian, 2006, Sohn et al, 2001). The advantage of using statistical methods is that a single vibration time history can be analyzed independently of all other signals collected elsewhere in the structure. This allows damage detection algorithms to be embedded at the sensor level, resulting in significant savings in power and computational time, both of which are necessary for the implementation of a fully wireless network. This method has been successfully

[1] Department of Civil and Environmental Engineering, Stanford University, Stanford, CA
[2] Risk Management Solutions, Newark, CA; formerly Department of Civil and Environmental Engineering, Stanford University, Stanford, CA

applied to numerically simulated damage to an experimental structure, such as the ASCE Benchmark Structure (Nair et al. 2006). However, computer simulations and even small-scale laboratory test structures cannot fully duplicate the dynamic response of actual structures. More importantly, the input ambient vibrations imposed on actual structures are much more random and unpredictable than those used in most computer and laboratory simulations.

In order to test the effectiveness of damage detection algorithms on actual structures a suitable experiment must be designed. Such an experiment either requires a full or near full-scale test involving large facilities or an actual structure that can be subjected to controlled damage tests. For this reason, suitable experimental data are difficult to find. However, recent progressive damage tests performed on the Z24 Bridge in Switzerland (Wenzel, 2003) provide a large amount of experimental data with which damage detection algorithms can be tested.

The purpose of this study is to test the robustness of the damage detection algorithm based on autoregressive time series modeling and statistical pattern recognition techniques, which were developed by Nair et al. (2006), Nair and Kiremidjian (2007) and Sohn et al. (2001), in detecting and quantifying structural damage induced by pier settlement, using acceleration data from the Z24 Bridge progressive damage test. In addition, several modifications have been made to the original algorithm to enable more robust diagnosis. This paper is organized in the following manner. First, the statistical pattern recognition methods for damage detection are summarized. A new damage measure based on the Mahalanobis Distance is introduced. Next, the bridge and data acquisition project are discussed. Finally, the results obtained from testing the algorithm on the Z24 Bridge data are presented and discussed.

Overview of Damage Detection Algorithm

Statistical pattern recognition based damage detection algorithms depend on the hypothesis that a structure's vibration time history will change with the onset of damage (Sohn et al. 2001, Nair et al. 2006). Because the time histories have complex signatures making them difficult to compare, it is desirable to extract features from the signal referred to as damage sensitive features (DSFs), with which damage can be tracked. Nair et al. (2006) have shown that decreases in a structure's stiffness due to damage will result in changes to AR coefficients for acceleration time series collected under ambient vibrations. Thus AR coefficients are an appropriate DSF.

Damage is evaluated according to a pattern classification framework. A pattern classification algorithm, according to Sohn et al. (2001) involves the following steps: (i) evaluation of a structure's operational environment, (ii) acquisition of structural response measurements and data processing, (iii) extraction of features that are sensitive to damage, and (iv) development of statistical models for feature discrimination. In this study the structural response measurements are acceleration time histories, and the DSFs are AR coefficients. Two methods for feature discrimination are proposed. Hypothesis testing using a t-test is performed as specified by Nair et al. (2006). In addition, a new multivariate damage measure (DM) based on the Mahalanobis Distance is proposed. The DM is also capable of measuring damage extent. However, identifying damage location is complicated and is beyond the scope of this paper. Each step in the damage detection algorithm is explained in further detail in the following sections.

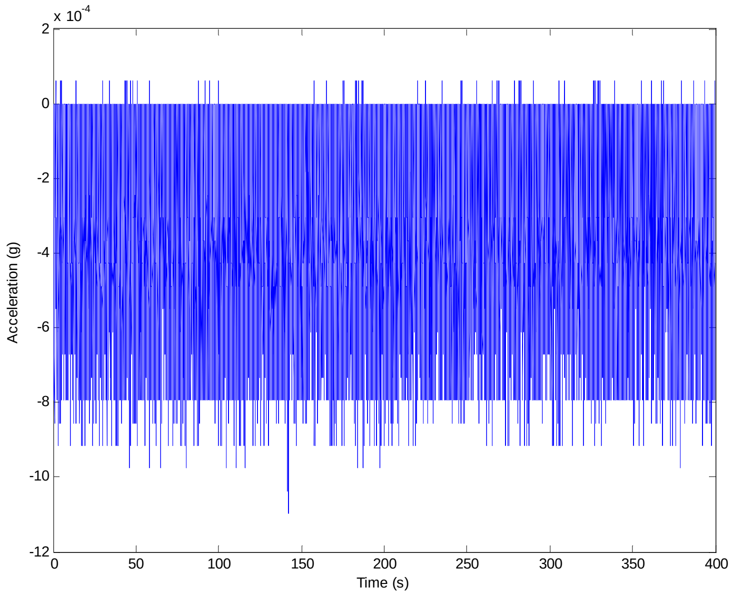
Data Preprocessing

Data preprocessing is done to remove or minimize dependence on variable environmental conditions and to identify conditions where sensors have probably malfunctioned. Acceleration time series collected from field experiments often show a drift in the signal. Linear drift is simple to correct. Nonlinear drift, however, is significantly more difficult to identify and correct (see Boore et al. 2006). In this paper, time series exhibiting nonlinear drift were discarded while those exhibiting linear drift were detrended. Linear drift can be removed by fitting a line to the signal using least squares methods and then subtracting that line from the signal, thus removing the trend.

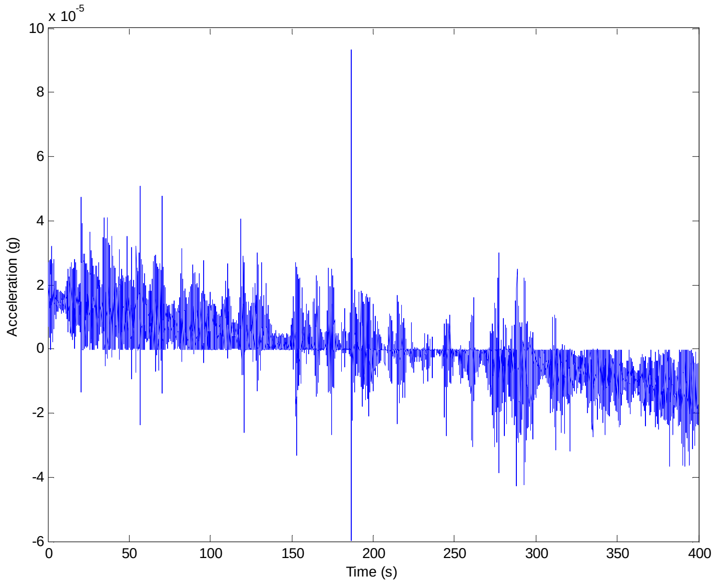
After detrending, additional preprocessing is done to minimize the dependence on load and environmental conditions. Sohn et al. (2001) show that normalizing and standardizing the acceleration time history by:

$$x(t) = \frac{(x(t) - \mu)}{\sigma} \tag{1}$$

where μ is the mean of the signal and σ is its standard deviation, is required in order to minimize the effect of load and environmental conditions on the AR coefficients. All time histories examined in this study are filtered using Eq. 1 prior to application of the AR model.



(a)



(b)

Figure 1. Examples of corrupt signals

As with all experiments, sensors may malfunction and produce corrupt data. Review of the data collected at the Z24 Bridge show that 298 out of approximately 4,000 acceleration time histories collected during the test were corrupted, representing only 7% of the database. Figures 1a and b show two examples of corrupt time histories. The signal in Fig. 1a appears to be clipped, while the signal in Fig. 1b is also clipped but at a constant value across the signal. As stated earlier, however, the majority of data did not display such problems and could be used in this analysis. Identification and correction of corrupted time histories, whether possible or not, is beyond the scope of this paper. Because the damage detection algorithm is a local sensor based algorithm, discarding corrupt signals does not affect the results presented in this paper.

Feature Extraction Using the Autoregressive Model

The AR model was presented in great detail in Nair et al. (2006) but is briefly summarized here for clarity. Let $x_i(t)$ be acceleration data from sensor i. $x_i(t)$ is divided into different chunks $x_{ij}(t)$ where i denotes the sensor number and j denotes the chunk. $x_{ij}(t)$ is standardized and normalized as described in the previous section.

Once preprocessing is complete, the optimal AR order must be estimated. In previous studies the autoregressive moving average (ARMA) model was used for modeling the vibration signal (Nair et al. 2006 and Nair and Kiremidjian, 2007). When analyzing the data, it was observed that results obtained from using the AR algorithm are not significantly different than those obtained using an ARMA algorithm. Therefore, to simplify the computations, the AR algorithm is used.

The AR model is given by the following equation:

$$x_{ij}(t) = \sum_{k=1}^{p} \alpha_k x_{ij}(t-k) + \varepsilon_{ij}(t) \tag{2}$$

where $x_{ij}(t)$ is the normalized acceleration signal of the j^{th} chunk of the i^{th} sensor, α_k is the k^{th} AR coefficient, p is the AR model order, and $e_{ij}(t)$ is the residual term. The Burg algorithm (Brockwell and Davis, 2003) is used to estimate the AR coefficients. Running the AR model on each chunk from a single sensor produces N vectors of AR coefficients of length p, where N is the total number of chunks from one sensor. Thus, it follows that

$$N = \frac{total\ signal\ length}{chunk\ length} \tag{3}$$

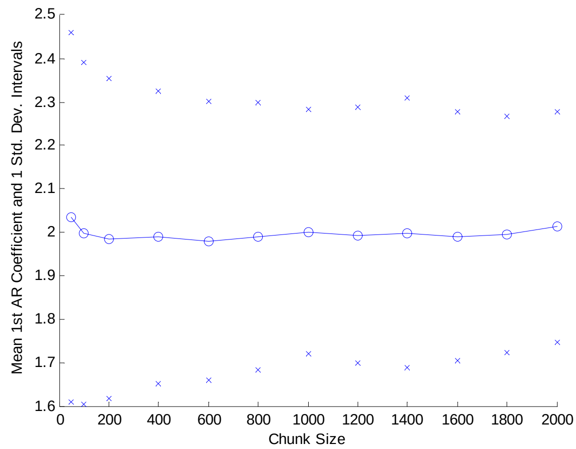


Figure 2. Variation of AR coefficients with data chunk size

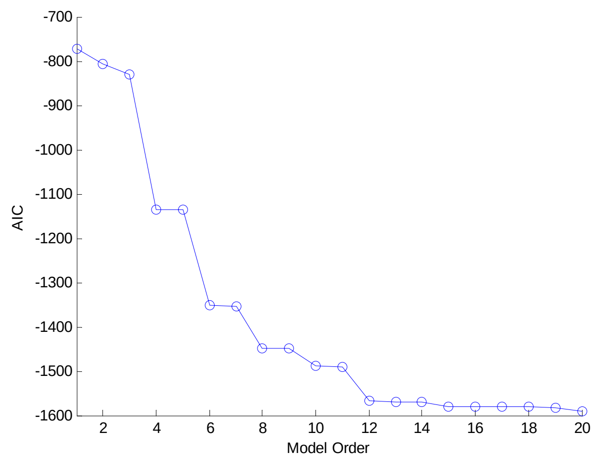


Figure 3. Analysis for optimal AR order

The optimal chunk length is determined by calculating the mean and standard deviation of the AR coefficients at different chunk length, and then determining at which point they begin to stabilize. Fig. 2 shows a plot of the mean of the 1st AR coefficient at varying chunk lengths. A chunk length of 400 was found to be optimal in this study. The optimal AR order can be estimated using the Akaike Information Criterion (AIC) as described in Nair et al. (2006). The optimal order is found to be in the range of 6-8 as shown in Fig. 3. In this study, an AR order of 8 is used.

The data are also tested for stationarity. For that purpose the residuals are investigated and the autocorrelation function of the residuals is estimated. It is found that with all the data, the time series appear to be stationary and the residuals are independent and identically distributed.

Feature Discrimination

The next step is to determine whether the feature vector has migrated from an undamaged baseline case to a potentially damaged state referred to as the test case. If the feature vector is determined to have migrated sufficiently in a statistically significant sense, then it is concluded that damage has occurred. It should be noted that for each baseline or test case, it is not merely one feature vector but rather N feature vectors that are being tracked. Thus, it is desirable to determine whether the cluster mean has migrated. This can be done using a standard t-test.

However, it is far from clear what level of confidence is necessary in order to conclude that damage has occurred. Previous research has shown that the use of q values representing the confidence level for migration of the mean values may overstate the significance of results by a large amount. Therefore, in order to develop a robust damage detection algorithm, some form of supervised learning must be used, with which the algorithm is trained using known damaged and undamaged data sets in order to develop a damage threshold beyond which it is concluded that damage has occurred. For this reason, calculating the q values and levels of confidence is not necessary. The t-statistic itself is used as a damage measure, and it represents a difference between population means weighted by the population standard deviations and the size of both data sets.

In order to perform the calculations, the proper damage sensitive feature must be formulated. As stated before, the DSF is a function of the AR coefficients, but defining this function is not trivial. After extensive study of the data, it was observed that the first AR coefficient alone is sufficient to capture the migration of the feature vectors. More complex combinations of AR coefficients tested did not significantly improve the performance of the algorithm, at least for the single variable t-test.

Figs. 4 and 5 show how the 1st AR coefficient varies with different amount of pier settlement at two different locations on the bridge deck. Figure 4 shows the variation of the 1st AR coefficient for the sensor located at mid-span of the bridge. Figure 5 shows the 1st AR coefficient for the east abutment. The bridge pier simulated settlement of 20mm, 40mm, 80mm and 95mm. The different symbols correspond to the base case (no settlement) and the different settlement values. There are N AR values for each settlement case and the baseline case corresponding to each data stream. The mean value of the 1st AR coefficient for each case is shown as a straight line. It can be observed that the mean value changes from the base line to each settlement case. The test procedure is described in greater detail in the application section of this paper.

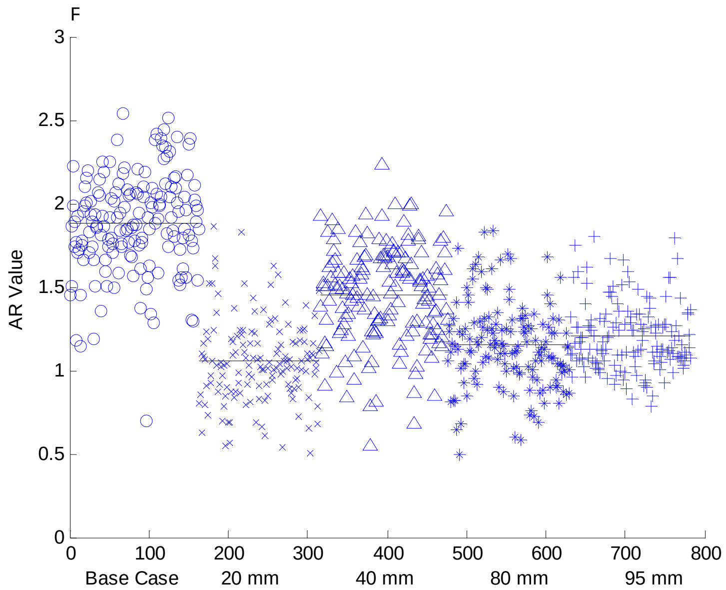


Figure 4. Variation of 1st AR coefficient with damage on mid-span sensor.

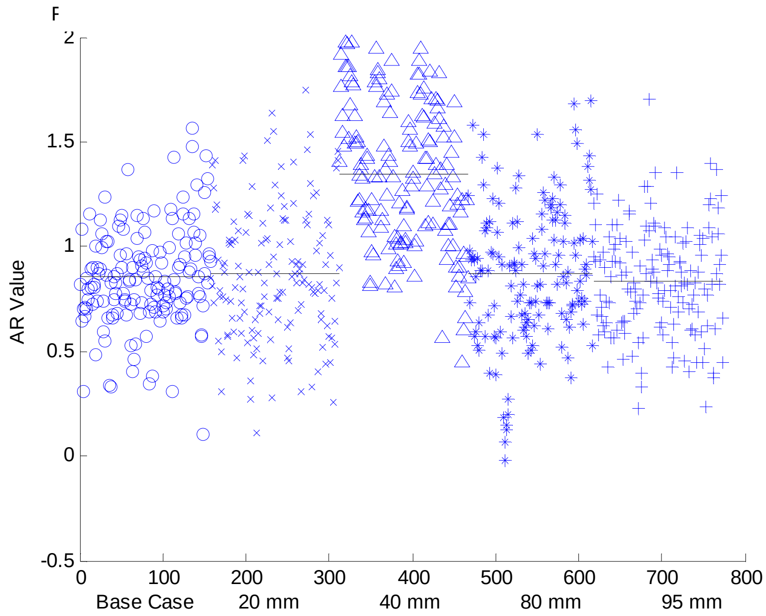


Figure 5. Variation of 1st AR coefficient with damage on east abutment sensor.

Another method of measuring the migration of the feature vector clusters is by computing the centroid to centroid distance between the undamaged cluster and test cluster. To do this, a new damage measure (DM) based on the Mahalanobis Distance is proposed. The Mahalanobis Distance between two clusters is given by the equation:

$$\Delta = \sqrt{(X-Y)^T \Sigma (X-Y)} \tag{6}$$

where X and Y are the centroids of each cluster, and Σ is the covariance matrix of one of the clusters. In order to take into account both clusters' covariance matrices and their cross covariance matrix, the DM is given by the equation:

$$DM = \sqrt{\left|(\mu_{\mathrm{undamaged}} - \mu_{\mathrm{damaged}})^T S_{\mathrm{inv}} (\mu_{\mathrm{undamaged}} - \mu_{\mathrm{damaged}})\right|} \tag{7}$$

where

$$S_{\mathrm{inv}} = \left(\Sigma_{\mathrm{undamaged}} + \Sigma_{\mathrm{damaged}} - 2\Sigma_{\mathrm{cross}}\right)^{-1} \tag{8}$$

$\mu_{\mathrm{undamaged}}$ is the centroid of the undamaged data set, μ_{damaged} is the centroid of the damaged data set, $\Sigma_{\mathrm{undamaged}}$ is the covariance matrix of the damaged data set, $\Sigma_{\mathrm{damaged}}$ is the covariance matrix of the damaged data set, and Σ_{cross} is the cross covariance matrix between each data set. In this application, the covariance and cross covariance matrices are reduced to scalars since only one AR value is used.

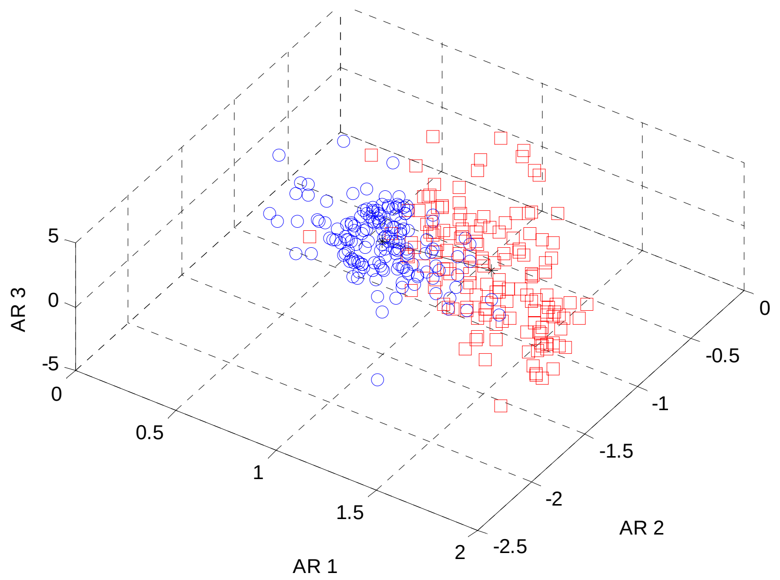


Figure 6. Clouds of the first three AR coefficients for the undamaged and damaged case. Blue are the undamaged data and red are the damaged data.

It is observed that the magnitude of the first three AR coefficients is significantly larger than the magnitude of subsequent AR coefficients; therefore only the first three AR coefficients are kept and the others are discarded. Thus it follows that the DM is a measure of distance between two clusters in 3 dimensional AR coefficient space. Figure 6 shows a plot of AR coefficient clouds from two separate damage setups. The value of the DM increases as the clouds migrate with damage.

Again, in order to detect damage, a form of supervised learning must be used, where the algorithm is trained to recognize damaged and undamaged data sets and thus develops a threshold value beyond which it is concluded that damage has occurred. Also note that the magnitude of the DM can be used to measure damage extent. This will be explained in further detail in the section presenting algorithm results.

Damage Detection Algorithm Summary

In summary, the damage detection algorithm is composed of the following steps:

1. Collect acceleration data from sensors located on an undamaged structure
2. Compute and store the AR coefficients as described above, including data preprocessing
3. Collect acceleration data from the same sensors at some later point in time
4. Compute the AR coefficients as described above, including data preprocessing
5. Perform feature discrimination techniques – calculate the t-statistic or the DM and compare the result with a previous training set – to determine whether the AR coefficient cluster has migrated sufficiently to conclude that damage has occurred

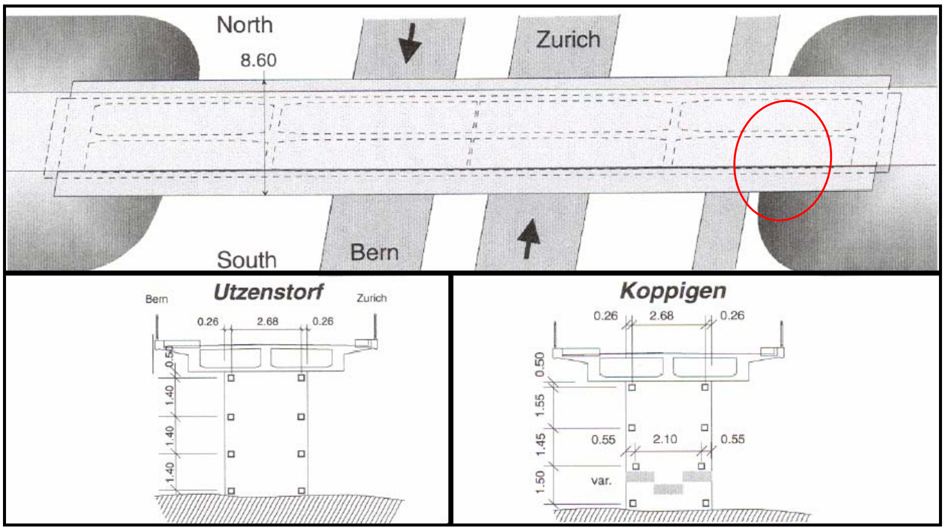


Figure 7: The Z24 Bridge with the Koppigen Pier circled

Application of Damage Algorithm to the Z24 Bridge in Switzerland

The damage detection algorithm was tested on data collected from a progressive damage test on the Z24 Bridge in Switzerland. The purpose of this study is to test the efficacy of the damage detection algorithm described above in discriminating between different controlled damage states to which the bridge was subjected.

Before its demolition, the Z24 Bridge spanned the A1 Berne-Zurich motorway linking Koppigen with Utzenstorf in Switzerland. The three-span structure had a total length of 58 m, subdivided in three spans of 14, 30 and 14 m, respectively. The superstructure consisted of a two-cell closed box girder with tendons in the three webs. Both main piers were built as concrete diaphragms, fully connected with the superstructure.

Prior to its demolition, the bridge was subjected to a number of progressive damage tests, one of which was induced pier settlement. In order to simulate settlement, one section of one pier was cut away and replaced by mechanical jacks, which were gradually lowered.

Damaged was introduced to the structure by gradually settling the Koppigen pier up to 95mm. The location of the pier is circled in Fig. 7. This settlement produced cracks in the deck as shown in Fig. 8. The cracks marked in red occurred when the settlement increased from 40 to 80mm. The cracks marked in blue occurred when the settlement increased from 80 to 95mm.

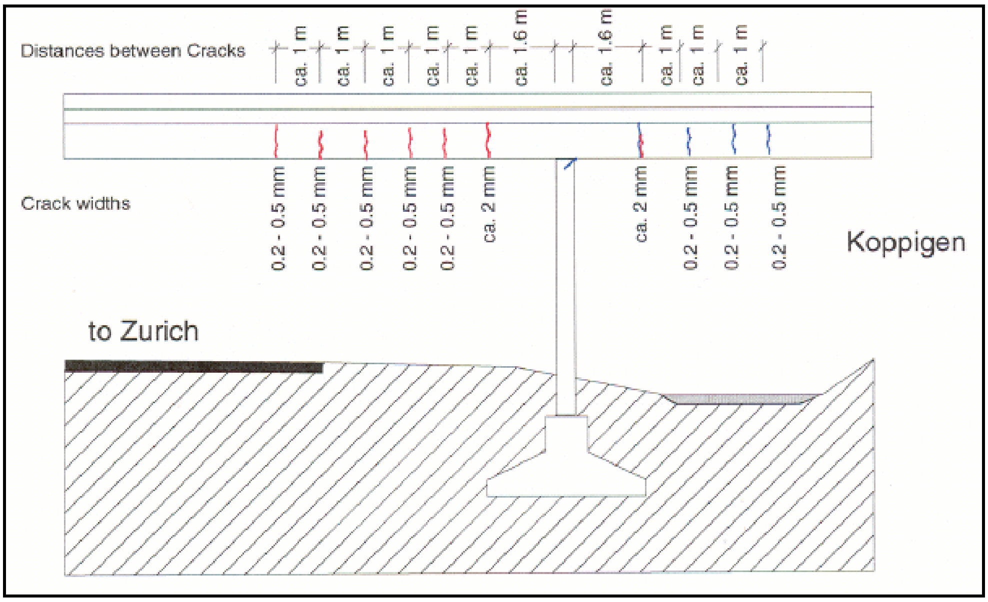


Figure 8: Cracks in the Z24 bridge after settlement

Acceleration data were recorded by sensors at various locations on the bridge, at ambient vibration conditions, after the bridge was subjected to each damage setup. Data were collected at a sampling rate of 100 Hz. Figure 9 shows the locations of the accelerometers on the bridge deck and piers. Acceleration was collected in the longitudinal, transverse, and vertical direction; however, because the damage detection algorithm compares characteristics of ambient vibrations, only results using vertical acceleration signals are presented. Results for longitudinal and transverse acceleration data are not appreciably different from the results for vertical accelerations.

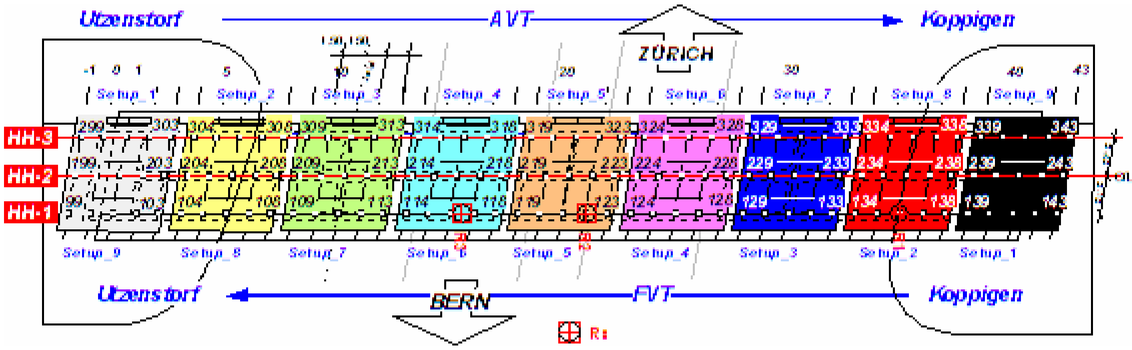


Figure 9: Location of Sensors Across Bridge Deck

In this paper, results are presented from the following six structural configurations:

Setup 1:	The original untouched structure.
Setup 2:	The structure after the pier settlement mechanism was installed in the Koppigen pier – used as the baseline
Setup 3:	20mm settlement in the Koppigen pier
Setup 4:	40mm settlement in the Koppigen pier
Setup 5:	80mm settlement in the Koppigen pier – cracks shown in red
Setup 6:	95mm settlement in the Koppigen pier – cracks shown in blue

Setup 2 is chosen as the baseline undamaged case, because all induced pier settlement occurs relative to that structural configuration. However, it is worth pointing out that large differences in the vibration characteristics of Setup 1 and Setup 2 indicate that the installation of mechanical jacks did change the structural characteristics of the bridge.

Table 1 shows the results of the application of the proposed damage detection algorithm to the Z24 Bridge data, using the t-test as the feature discrimination method, for the four damage setups compared to the undamaged baseline. In order to reduce the amount of data, only results from one out of every five sensors, evenly spaced across the bridge, deck are presented (although some are missing due to sensor malfunction). It is evident that the magnitude of the t-statistic does not increase monotonically as the level of pier settlement increases. By visual inspection, it is easy to see that the magnitude of the t-statistic corresponds roughly to the distance between population means.

Tables 2 shows the results of the damage detection algorithm using the damage measure as the method for feature discrimination. The results correspond roughly with those found using the t-statistic. Thus both methods in this case are shown to have roughly equivalent results. Also, the results found using only the first AR coefficient do not change appreciably when the second and third AR coefficients are included.

Table 1 – T-Statistic Values for Various Sensor Locations

Pier Settlement				
Location	20 mm	40 mm	80 mm	95 mm
101	-8.4728	-8.0544	-17.775	-14.068
201	-1.8652	-1.6071	0.26049	-5.8201
301	-10.775	-14.978	-13.209	-14.382
106	2.9852	-0.86767	-2.0425	5.6667
206	-0.47826	3.3337	-1.1282	2.7624
306	0.57788	3.2537	2.013	4.2237
116	-27.757	-13.18	-30.266	-24.061
216	-24.014	-1.7335	-17.844	-17.839
316	-28.605	-8.1421	-24.704	-27.053
121	-15.285	-1.1558	-25.361	-20.213
221	-8.9989	-7.864	-10.476	-10.015
321	-14.587	-3.2537	-21.144	-21.191
126	-20.17	-6.1549	-26.831	-19.308
226	-16.57	-13.627	-15.946	-12.091
326	-18.886	-0.21813	-21.485	-15.859
131	-26.102	-18.821	-38.7	-22.382
331	-29.84	-14.171	-43.926	-29.577
136	2.5772	8.7144	-6.4161	-1.9511
236	0.65151	-3.5583	0.15119	-2.1021
336	0.56665	15.422	-2.617	-2.0823
141	-33.215	-24.431	-34.981	-31.556
241	11.4	5.227	5.3618	8.9447

Table 2 - DM Values for Various Sensor Locations

Pier Settlement				
Location	20 mm	40 mm	80 mm	95 mm
101	1.3672	1.4605	2.2543	1.4984
201	2.8148	1.6477	2.315	2.0303
301	1.8038	1.2464	1.7412	1.5377
106	0.65756	1.017	0.48665	0.6316
206	0.52101	0.44036	0.47101	0.47405
306	0.4377	0.31049	0.57926	0.49879
116	2.2801	1.5579	2.6068	2.0127
216	2.3229	0.94676	2.0415	1.9726
316	2.3958	0.69174	1.9713	2.432
121	1.3982	0.38262	2.3657	2.0281

221	1.4601	0.74145	1.3769	1.3197
321	1.367	0.31342	2.0755	1.9498
126	1.8446	1.3021	1.9623	1.7476
226	1.9327	1.3421	1.7605	1.3974
326	1.6008	0.035737	1.6585	1.3607
131	2.0923	2.329	3.283	1.8576
331	2.4946	1.2983	3.8846	2.5527
136	0.41529	2.1663	1.4386	0.57049
236	0.60495	2.9938	0.91662	0.62481
336	0.58715	1.4109	1.072	0.54924
141	2.8593	2.7104	3.8384	2.8578
241	1.0373	4.4565	2.0956	1.0589

Again, it is observed that the damage measure does not increase monotonically with pier settlement. This is because of the occurrence of cracking in the bridge girder between 40 and 80 mm pier settlement and again between 80 and 95 mm settlement. The presence of cracking reduces the built up stresses in the bridge girder. Therefore, the 80 mm pier settlement case should be considered as another completely different damage case, instead of a more extreme version of the 20 and 40 mm damage cases. Likewise, the 95 mm damage case should be considered as a separate damage case, although it is reasonable to expect, and the results confirm, that it is similar to the 80 mm case.

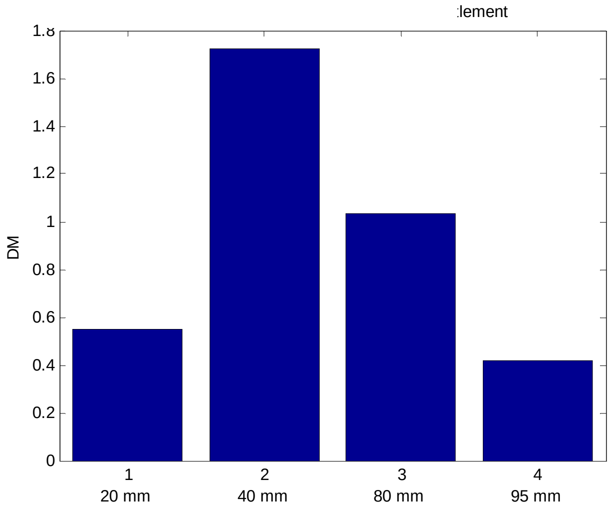


Figure 10. Damage measure, DM for different pier settlements

Figure 10 shows how the DM varies as pier settlement increases, for a typical sensor near the east abutment. One way of interpreting the results is that as the pier settlement occurs initially stresses build up in the bridge girder, which cause the DSFs to migrate. At 40 mm settlement, the DSF migrates farther. However, once cracking occurs between 40 and 80 mm settlement, the stresses are released and the DSF returns to near-undamaged levels. Note that this effect only occurs in the east span sensor and pier settlement occurs in the east pier. By observing the way different sensors respond to damage by location in the structure, it may be possible to develop a procedure to localize damage. Again this would most likely have to be done by some sort of supervised learning process. Without additional data and testing, it is not feasible to explore this topic further in this study.

Conclusion

This study demonstrates that a damage detection algorithm based on a pattern classification framework can detect structural changes caused by damage, using data collected from a real structure. However, it is emphasized that the damage detection algorithm proposed, in practice will require a training data set in order to better distinguish between damaged and undamaged samples. In practice, this may be difficult to accomplish because of the high expense involved with intentionally damaging an existing structure. Nevertheless, a library of various structures' responses to different damage patterns can be built over time for purposes of training damage detection algorithms. This may be used in order to diagnose and eventually localize damage.

In addition, it is emphasized that the response of the DSF to a given damage pattern changes significantly with the location of the sensor on the structure. (Where was this discussed or shown in the paper?) Furthermore, the effects of damage to a large structure are often complex. Increasing levels of one type of damage may not result in a monotonically increasing damage measure; therefore, the migration of DSFs must be handled carefully.

Acknowledgements

This research was partially supported by the National Science Foundation through the NSF-NEESR Grant – 15BBK16379 and by a grant from the National Institute from Standards and Technology, ATP 2005. The authors gratefully acknowledge their support.

Reference

Nair, K.K., and Kiremidjian, A. S. (2007). "Time Series Based Structural Damage Detection Algorithm Using Gaussian Mixtures Modeling", *ASME Journal of Dynamic Systems, Measurement, and Control*,129,258-293.

Nair, K.K., Kiremidjian and K.H. Law. (2006). "Time Series Based Damage Detection and Localization Algorithm with Application to the ASCE benchmark Structure," *Journal of Sound and Vibration* 291, 349-368.

Sohn, H., Farrar, C.R., Hunter, H.F. and Worden, K., (2001), "Applying the LANL Statistical Pattern Recognition Paradigm for Structural Health Monitoring to Data from a Surface-Effect Fast Patrol Boat", *Los Alamos National Laboratory Report LA-13761-MS,* Los Alamos National Laboratory, Los Alamos, NM 87545.

Brockwell, R. J. and Davis, R. A. (2003). *Introduction to Time Series and Forecasting, Springer*, 2nd Ed., 456p.