Structural Health Monitoring: A Quest towards the Use of Combined Approaches

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STRUCTURAL HEALTH MONITORING: A QUEST TOWARDS THE USE OF COMBINED APPROACHES

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ABSTRACT

Over the past number of decades the structural health monitoring (SHM) research community has developed and published a large variety and number of methodologies for the purpose of detecting and locating damage in a structure using sensor measurement data. While almost all of these methods have demonstrated some degree of success in detecting damage, different approaches have differing costs, and corresponding tradeoffs in performance. Typical costs include computational effort, the development of an accurate structural model, or the collection of a large volume of data. Whether or not these costs are worth the investment depends on the specific SHM scenario. In this paper we analyze four different SHM methodologies, including model-based and data-based approaches, outlining their individual strengths and weaknesses, tradeoffs between cost and performance,and suggesting appropriate application areas for each. The efficacy of the methods is evaluated using data collected from a steel-frame laboratory structure.

KEYWORDS : *Feature extraction, Data fusion, Statistical methods*

INTRODUCTION

The goal of structural health monitoring (SHM) is to provide information on the condition of a structure by deploying a network of sensors to gather information. While there are many possible approaches to SHM, the economics and constraints of individual scenarios will dictate which approach is most suitable. No one strategy is likely to be best in all scenarios. With this in mind, in this paper we present four different methodologies, each with a specific scenario in mind. This is not intended as a comprehensive review of all possible ways of approaching the SHM problem, but instead as an exploration of how different constraints can impact the accuracy and reliability of SHM. In general we can consider two different approaches to SHM, model-based and data-based.

Model-based approaches observe the differences between the measured response of the actual structure and the response predicted by the model, however quantifying the cause of these differences requires the solution of an inverse problem, a costly and difficult operation. Also, they require an accurate model of the structure to be monitored. The first method presented in this paper aims to overcome some of the computational difficulties associated with model-based approaches by using a simplified model in conjunction with a quasi-real time Kalman filter to estimate and update the mass and stiffness properties of the structure.

When a full or even simplified model is not available for the structure, there still might be some structural information that can be taken advantage of for the purposes of damage detection. As a simple approach, if the structure can be assumed to act similar to a beam, an analysis based on the measured mode shape curvature can provide information on the presence and location of damage. If the structure is more complex, then this methodology will not be particularly sensitive to damage.

Data-based approaches offer a more flexible solution to SHM. These approaches typically consist of data acquisition, followed by the extraction of damage-sensitive features and finally statistical processing to compare new features with a database from the baseline condition of the structure. Again, the specifics of the scenario dictate how we approach the problem. For wireless sensor networks it is often costly to transmit full time histories, and there can be significant benefits in embedding a micro-controller at the sensor level to perform computation prior to transmission. In such a system, computational effort is a key consideration, and efficient algorithms are required. The third approach presented in this paper has been developed for this purpose, and combines auto-regressive analysis with one-class machine learning. However, the requirement for low computational effort may limit the accuracy of this approach.

There is a natural tradeoff between efficiency and accuracy, and given more computational power we may be able to detect and localize damage more precisely. The fourth approach presented here is a relatively computationally expensive data-based method which uses nonlinear based damage indices to detect and localize damage. In comparison to the low-cost embedded method, where features can be computed without wireless transmission, we are unlikely to have a large database of features from the baseline structure for statistical comparison. Therefore, we propose a statistical distance-based method which is suitable for use with smaller datasets in combination with the nonlinear damage indices.

These methods are evaluated by conducting experiments on a steel-frame laboratory structure in its intact state as well as in two different damage states, induced by loosening bolted connections. This analysis allows us to compare how the tradeoffs mentioned above affect the accuracy and reliability of damage detection and localization.

1 DAMAGE DETECTION ALGORITHMS

1.1 Model-based Unscented Kalman Filter Method

As a model-based damage detection method, the unscented Kalman filter based damage detection method is applied for comparative studies [1]. The unscented Kalman filter (UKF) has been applied to identify simple structural systems which have a small number of degrees of freedom (DOF) and the method detects damages in the structural system based on identified structural properties [2]. UKF approximates the posterior probability density by a Gaussian density represented by carefully chosen sigma points. The sigma points determine the true mean and covariance to the second-order of nonlinearity when sigma points are propagated through a nonlinear transform.

1.2 Mode shape curvature

When models of the structure are unknown or unavailable, operational mode shapes can still be measured from the collected vibrational data. Mode shape has been used as a damage detection metric, based on the fact that changes in a structure or damage will cause changes in the vibrational mode shapes. An issue is that the difference between the mode shape of an intact and a damaged structure, is not particularly sensitive to damage, however the second derivative of a mode shape, the mode shape curvature provides a better damage metric [3, 4, 5]. A simple Euclidean distance of the mode shape curvature between the intact and damaged cases is used as the damage metric. Error bars on this metric are derived from multiple measurements. The drawbacks to this method are that it relies on data from multiple sensors and numerical differentiation which is subject to noise. Mode shape curvature may only be useful as a metric with a structure similar to a beam; with more complex structures, interpretation of the data is less meaningful.

1.3 Low-cost machine learning based damage detection

In this section, a data-driven approach to damage detection at the individual sensor level is presented which places an emphasis on low computational effort and is suitable for embedded computation on a microcontroller. In the data-driven approach damage-sensitive features are extracted from acceleration time series, and statistical pattern recognition is then carried out to distinguish whether the extracted damage sensitive features are abnormal. The statistical pattern recognition methodology presented in this section is based on the one-class support vector machine (OCSVM), a nonparametric machine learning method for novelty detection. This approach is a 'sensor local' approach, meaning features are extracted for an individual sensor, and pattern recognition is carried out locally, independent from any other sensor locations.

The desire for computationally efficient 'smart sensing', places a number of constraints on the feature-extraction process. While a significant research effort has been dedicated to the suggestion of damage-sensitive features for structural damage detection, many of these features are not appropriate for embedding at the sensor level. Specifically, in addition to being sensitive to damage, and robust with respect to benign ambient variations, features should also require low power for computation, should only require data from one sensor location, and ideally should exhibit sensitivity with proximity to the damage location, in order to allow localization.

The auto-regressive model estimated using Burg's method has previously been suggested [6] as a means for efficient, embeddable feature extraction. The simple AR(p) model is given by:

$$x(t) = \sum_{k=1}^{p} \alpha_k\, x(t-k) + e_x(t) \tag{1}$$

where x(t) is a single acceleration time series, α_k are the autoregression coefficients, p is the order of the model, and $e_x(t)$ is the residual error. The first five coefficient are chosen as the damage sensitive features. As each sensor location has three axes of vibration, a 15 dimensional feature vector is formed for each sensor location, i, as follows:

$$FV_i = \left[\alpha_{1x}\ \alpha_{1y}\ \alpha_{1z}\ \alpha_{2x} \ldots\ \alpha_{4z}\ \alpha_{5x}\ \alpha_{5y}\ \alpha_{5z}\right] \tag{2}$$

where FV_{ij} is a feature vector for the i^{th} sensor corresponding with one test and α_{1x} is the first AR coefficient in the x direction of vibration.

The OCSVM is a state-of-the art, non-parametric, machine learning algorithm for novelty detection [7]. In order to calculate a decision boundary, the OCSVM is trained on a set of baseline feature vectors, from what is assumed to be a safe condition of the structure. The training process generates a nonlinear decision boundary, which can then be used to output a binary decision, when given new feature vectors, indicating whether they are from the normal condition of the structure, or from an anomalous condition. The use of the OCSVM for novelty detection in structural health monitoring was demonstrated in [8]. Once trained on the baseline data new data points, x, can be evaluated by the following functions.

$$f(\mathrm{x}) = \mathrm{sgn}\left(\sum_{\mathrm{i}}^{\#SVs} \alpha_i \mathrm{K}(\mathrm{x}_i, \mathrm{x}) - \rho\right) \tag{3}$$

$$\rho = \sum_j \alpha_j\ \mathrm{K}\left(\mathrm{x}_k, \mathrm{x}_j\right),\quad \alpha_j \in \left(0,\ \frac{1}{\nu N}\right) \tag{4}$$

A distance metric can also be evaluated by simply dropping the sign function in front of the above equation. This is useful for damage localization purposes as it not only tells us whether a point is abnormal with respect to the data from the healthy structure, but also how abnormal it is. To make the localization index more intuitive we invert the sign, so that high positive values indicate more severe damage, and negative values indicate no damage.

$$LI(\mathrm{x}) = -1\left(\sum_{\mathrm{i}}^{\#SVs} \alpha_i \mathrm{K}(\mathrm{x}_i, \mathrm{x}) - \rho\right) \quad (5)$$

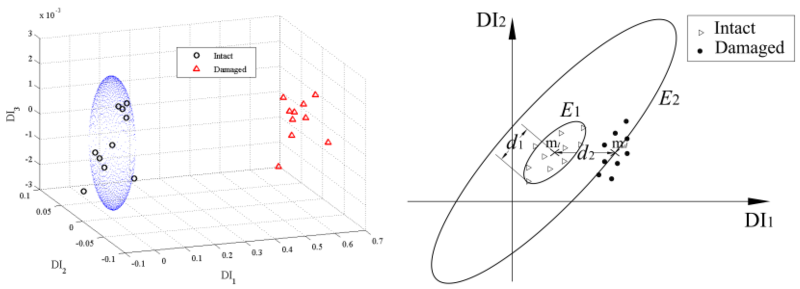
1.4 Energy Based Non-Linear Algorithm

If computational effort is not a key concern, for example in a scenario when raw data is transmitted to a base station prior to computation, more sophisticated tools can be used for feature extraction. In this scenario, we expect the volume of data to be a limiting factor, as transmission of full time series is a costly operation. The previous algorithm dealt with a scenario where computational effort was of high importance, but the volume of data was expected to be large. In contrast, the algorithm presented in this section is applicable for small data sets, where high precision is desired. This can be seen as a tradeoff between data size and computational effort: If the data set is large we may not require high computational effort to achieve satisfactory results, but if the data set is limited, more effort, and more sophisticated feature or damage index (DI) extraction, will be needed.

In general, achieving high precision with a small data set requires the extraction of more sensitive DIs. With this in mind, we focus on some nonlinear effects of a certain type of damage, called an active discontinuity [9]. We use an energy-based method, to capture the nonlinear effects of this damage. A necessary condition for reliability of any energy-based method is to avoid the leakage of energy. To satisfy this requirement, we employ the Hilbert Huang Transformation (HHT), a nonlinear signal processing tool. HHT guarantees that there is no leakage of energy due to the imposition of spurious harmonics on the expansion of a signal; an inevitable drawback of Fourier and wavelet transformations [10]. Using HHT, a certain energy distribution curve can be defined under the condition of consistency of excitation and input energy. This energy distribution is called normalized cumulative marginal Hilbert spectrum (NCMHS) which can be regarded as a reliable signature for the structure [9].

Using only the raw sensor data this algorithm can identify the closest sensor(s) to the damage location. First, we test the structure in its intact or presumed reliable state. Using this data, a baseline NCMHS is first computed for each sensor simply by taking the mean value or median. Then, the energy distribution for each sensor data of the test structure is computed. Any measure of discrepancies between the baseline signature at each sensor location and the NCMHS of the test structure for the same location can be regarded as a DI [9].

To monitor the structure, the actual discrepancy is computed with the expected discrepancy from the baseline. The expected discrepancies are obtained by comparing the data from the intact structure with the baseline. Combining the DIs a feature vector can be formed for each test and each sensor location. For more than one test, we obtain two clusters in an m-dimensional feature space, one for the intact and the other for the test structure; where m is the number of DIs used. Such clusters are shown schematically for a three-dimensional space and three DIs in Figure 1a.



(a) **(b)**

Figure 1: (a) Two clusters of feature vectors for a structure before and after damage; (b) Sensitivity of Euclidian and Mahalanobis distances when some of the DIs are not sensitive to the damage

Although this nonlinear energy-based algorithm can be used with few samples, the computational effort of this method is higher due to the use of the HHT. A distance-based approach can also be used for comparing two clusters in order to improve the efficacy of the algorithm for small data sets. To localize the damage, we assume that the damage is more probable to be in the neighborhood of the location with higher distance between the clusters. Mahalanobis distance can be chosen as the measure of discrepancy between clusters because of its ability to differentiate between two clusters even when some of the DIs are not affected by the damage. This property is shown in Figure 1b by comparing the Euclidian and Mahalanobis distances. We observe that the Euclidian distance between the furthest point and the mean value of the intact cluster is almost equal to the distance between the mean values of the two clusters in such a case that DI_2 is not sensitive to damage. However, Mahalanobis distance represented by the ellipsoids can effectively capture the difference between two clusters. Computing this distance for each sensor identifies the sensor locations in the vicinity of the damage.

2 EXPERIMENTAL SETUP

To generate data for comparing the performance of different damage detection algorithms, a model structure was used for experimentation. A modular steel structure was tested in a 3 story 2 bay configuration. The structure consists of columns that are 60 cm x 5.08 cm x 0.64 cm and beam frames of similar dimensions for each story. The parts are bolted together at each connection with four bolts and the whole structure is bolted to a heavy concrete foundation as a reaction mass. The structure is shown in Figure 2.

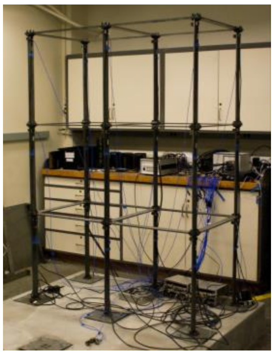


Figure 2: Model Structural System

Table 1: Damage Scenarios and Locations

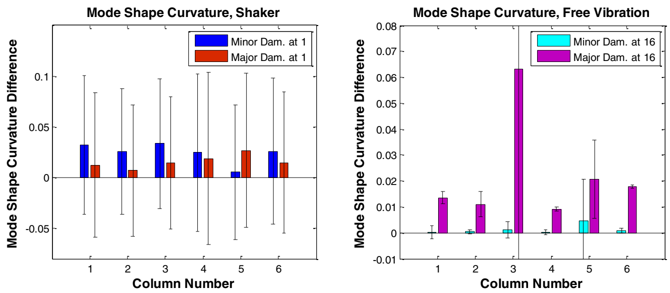
Excitation	Damage	Damage Description	Location
Both	None	No damage	-
Shaker	Minor	2 bolts slightly loosened	Sensor 01
Shaker	Major	4 bolts loosened	Sensor 01
Free Vibration	Minor	2 bolts removed	Sensor 16
Free Vibration	Major	4 bolts loosened	Sensor 16

To measure the vibration response of the structure, 18 piezoelectric triaxial accelerometers were attached at locations near the 18 connections. This gives a total of 54 acceleration time signals from the structure which are sampled at 6000 Hz. To excite the structure, two different sources were used, either free vibration after an initial displacement, or small shaker attached to the top corner of the structure which provided a random white Gaussian noise in a frequency range of 5 - 350 Hz in the flexible direction. There were three different damage scenarios involving the bolted connections, forming different levels of damage: two bolts slightly loosened, two bolts removed, four bolts loosened. The damage scenarios and locations are summarized in Table 1.

3 RESULTS AND DISCUSSION

3.1 Mode Shape Curvature

For this specific structure, the mode shape curvatures are calculated for each one of the six columns in the structure. This should give some localization of the damage. For the free vibration test data the results are shown in Figure 3a. For the shaker test data the results are shown in Figure 3b. The detection of minor damage in the form of removing two bolts is not possible in most cases, even at the location of the damage. With the data from the shaker excitation the structure is not detected as damaged because the error bars on the damage index are too large, which may be due to the large variability of the shaker excitation. Under free vibration however, detection of the major damage case of four bolts loosened is marginally possible.

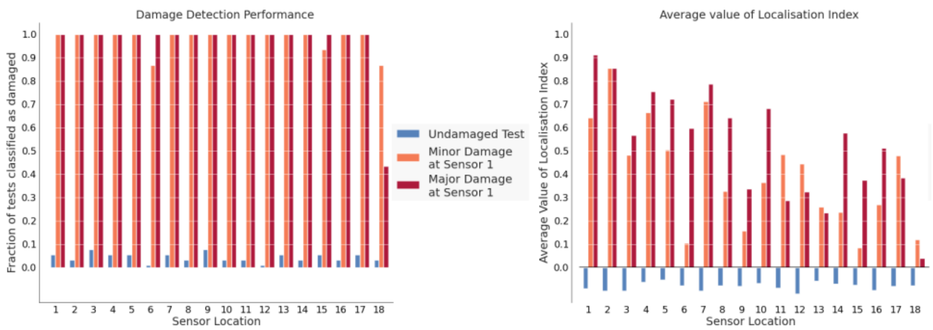


(a) (b)

Figure 3: Mode shape curvature damage detection results for (a) shaker and (b) free vibration test data

3.2 Low-cost machine learning based damage detection

A database of 258 ten second samples is used to establish the baseline condition of the structure. These raw acceleration signals are processed into a 15 dimensional feature vector for every sample, at each sensor location as described in Section 1.3. The baseline data is pre-processed to have zero mean and unit variance, and the OCSVM classifier is then trained using this data. New test points are then preprocessed in the same manner as the training data, before being evaluated by the trained OCSVM.



(a) (b)

Figure 4: (a) Damage detection using low-cost machine learning based method, (b) damage localization using the OCSVM localization index.

Figure 4a shows the fraction of tests classified as damaged, for each sensor location, for the minor and major damage scenarios at sensor 1. For comparison, the fraction of tests from the undamaged structure classified as damaged are also plotted. While the damage detection performance is excellent, for both minor and major damage cases, we can see that the simple damage detection process does not provide any information on the location of the damage.

Regarding localization of the damage, in Figure 4b above, the average values of the localization index for the same scenarios are shown. In the case of the minor damage we see that the value of the localization index is highest at Sensor 2, followed by sensor 4, 7, and 1. Locations 2 and 4 are adjacent to the damage location at sensor 1 and thus the localization index provides valuable information on the location of the damage. For the major damage at sensor 1 location, the highest average value of the LI is observed at sensor 1, effectively localizing the damage.

3.3 Energy Based Non-Linear Algorithm

The same damage scenarios as in Table 1 are used for verification of the nonlinear energy-based damage detection algorithm. However, only 10 tests for each scenario are considered in order to model the case with small data set. The excitation for all these tests is the free vibration in the flexible direction.

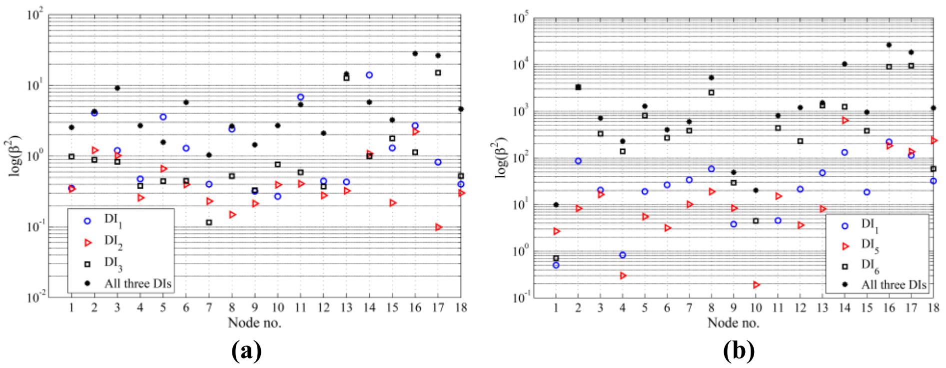


Figure 5: Logarithm of Mahalanobis distance between two clusters at each sensor location; a) minor damage at 16; b) major damage at 16

Figure 5 shows the logarithm of the squared Mahalanobis distance between two clusters at each sensor location. The results in this plot are for each DI separately and combination of all DIs as in a feature vector. Generally, the distance is at least one degree of magnitude higher at the location of damage and some of its adjacent nodes. Based on the results, consideration of several DIs has many benefits. For instance, in the case of minor damage at node#16, DI_1 gives us unsatisfactory results. However, the localization is accurate if we consider the entire DIs simultaneously.

CONCLUSION

This study proposes and compares different algorithms for the detection and localization of structural damage. Factors such as the level of precision necessary for detection and localization, importance of the structure, the size of data set, computational effort allowable, and sensor network limitations determine which method is most suitable for a given SHM problem.

The unscented Kalman filter based monitoring algorithm as a model-based SHM methodology could be used to quickly detect inconsistency in the structural behavior. Building an accurate model may not be feasible or justifiable for most mechanical systems; therefore, data-based algorithms are more practical in general applications. There is always a tradeoff between the precision of the results and the computational effort. We have proposed two data-based approaches for two different cases: 1) the low cost machine learning-based algorithm when the data set is large and the computational effort is of high importance, 2) energy-based nonlinear algorithm when the data set is small and the constraint is on the precision. Clearly, the second algorithm needs higher computational effort to satisfy the criteria.

Experimentally verified results show that both data-based algorithms can effectively detect the damage which cannot be detected using the simple mode shape curvature method. The machine learning-based algorithm needs a large data set and it is not as accurate as the energy-based algorithm for localization of damage; however, the machine learning algorithm is computationally more efficient. Such efficiency results in its applicability to be used in smart sensors so that the algorithm can be run in the sensor before transmitting the data. Table 2 gives a comparison between the proposed algorithms and the simple mode shape curvature algorithm.

Table 2. A comparison between the damage detection algorithms

Algorithm	Sensor connections	Model	Computational effort	Detection	Localization
Unscented Kalman Filter	Yes	Yes	Low	Quasi-real time	Not very precise
Mode shape curvature	Yes	No	Low	Marginal	Not satisfactory
Machine Learning-based alg.	No	No	Moderate	Excellent	Good for major, okay for minor
Energy-based Nonlinear alg.	No	No	High	Excellent	Good for both cases

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