MONITORING INFRASTRUCTURAL HEALTH: IN-SITU DAMAGE DETECTION AND LOCALIZATION UTILIZING DISTRIBUTED SMART SENSOR TECHNOLOGY

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Abstract

The rapid development of inexpensive "smart" remote sensing devices has triggered the onset of a revolutionary transformation in data acquisition and reconnaissance paradigms. Referred to as simply a mote, these devices integrate a microprocessor, computational memory, and a radio transmitter into one small battery operated instrument. Deploying large ensembles of motes equipped with sensors could allow for coordinated decisions based on data shared within dynamic adhoc networks or simply as autonomous devices. Since the mote-sensor combination has the ability to virtually listen, think, and talk the development of a smart wireless sensor network is an advantageous prospect for the monitoring field. Recent studies have shown that transmitting large amounts of data over the fragile communication radio links is not viable for real-time monitoring. Data loss has been attributed to the low bandwidth of the low power radio transmitters employed on motes and is seen as a permanent hurdle. Despite the progress made by new transmission protocols and standards towards increasing radio bandwidth, this improvement alone will not meet all of the needs of a full-scale wireless monitoring system. As such the scope of this work is on decentralizing an infrastructural monitoring system by exploiting the on-board computational faculties of a mote.

Introduction

To date smart wireless sensors (SWS) and smart wireless sensor networks (SWSN) designed for civil structural health monitoring (SHM) applications have been configured to operate in a fashion consistent to that of centralized data acquisition systems of which they are envisioned to replace. Several researchers (Xu *et al.* (2004); Paek *et al.* (2005); Caffrey *et al.* (2004)) have shown that complex routing and compression algorithms can be embedded onto commercial mote platforms to increase their transmission reliability, an intrinsic limitation associated with low power data transmission, yet the end objective has been to send all data to one centralized collection center for intensive post-processing. From a structural engineering standpoint the intensive processing required for data compression and routing is not seen as the best use of both the present mote's limited power and computational resources for structural health monitoring applications.

In fact, despite recent advancements in wireless radio transmission standards/protocols (Bluetooth, ZigBee) better radio specifications themselves do not appear to be able to support the high data acquisition/transmission rates required for vibration-based health monitoring, especially for dense sensor networks. That is to say that transmission power consumption, radio bandwidth, and latency attributed to data compression schemes will continue to stand in the way of the development and implementation of a full–scale SWSN for SHM. As such, novel distributed SHM algorithms which extract meaningful features from response data at each sensor node, i.e. without multiple channels of data, need to be developed and embedded onto motes.

Based on the comprehensive reviews of SHM techniques by Doebling *et al.* (1996) and Sohn *et al.* (2004) and considering the present state-of-the-art capabilities of motes, feature correlation-based health monitoring schemes appear to be well suited for distributed process SHM for SWSN.

Correlation-based Health Monitoring

Perhaps Cawley & Adams (1979) presented one of the first types of correlation techniques to be used for damage localization. Their technique compared ratios of consecutive natural frequencies obtained experimentally with those obtained using a numerical model. Later, Lew (1995) focused on evaluating changes in system transfer functions and presented the vector inner product as a correlation metric for damage detection. Then, Messina *et al.* (1996) developed a natural frequency based localization procedure and metric know as the Damage Location Assurance Criterion (DLAC). The DLAC metric was based on the modal assurance criterion (MAC) which is a measure of linear correlation between an experimental and analytical mode shape and is typically used for validating the fidelity of an analytical model. Hence, the metric is very similar the inner product vector operation. In their work Messina *et al.* (1996) showed that the MAC concept can be to extended damage localization by comparing natural frequency characteristics of a model with those obtained from the actual structure.

A noteworthy drawback to many direct correlation-based monitoring techniques is that all, or nearly all, of the hypothetical damage cases must be numerically generated and appropriately databased in order to reliably detect and localize damage. If a complex structure is to be monitored and multiple damage scenarios are considered the database of damage cases can become immense and its generation is a computationally intensive process. In response to this shortcoming more sophisticated correlation methods have been introduced which aim to reduce the database size without diminishing localization accuracy. Recently researchers (Koh & Dyke (2005); Messina *et al.* (1998); Lam *et al.* (2006); Qian *et al.* (2006)) have developed genetic algorithms or statistical-based recognition methods such as probabilistic/artificial neural networks (P/ANN) to detect and locate multi-site damage scenarios without massive databases. Considering diurnal fluctuations in modal parameters and the uncertainties associated with ambient vibration-based modal identification techniques these types of methods appear to be one of the best options for the future of health monitoring; however, these methodologies are perhaps too computationally intensive for commercially developed motes at this present time.

In this work a numerical sensitivity analysis is conducted using the DLAC direct correlation metric with the objective of incorporating the technique into part of a SWSN ready distributed SHM algorithm for monitoring simple structures. In Messina *et al.* (1996) initial study introducing the DLAC metric the reliability of the correlation procedure was investigated with respect to modal truncation and the percent of imposed damage. This study is focused on reducing the required hypothetical damage database for a simple cantilever beam structure which is planned to serve as the experimental testbed for subsequent real-time monitoring with a SWSN. As such, the efficacy of the DLAC will be analyzed with respect to *spatial quantization*.

DLAC Sensitivity Analysis

Spatial quantization as it is conceptualized here is the condensation of the actual structure's infinite degrees of freedom to that of the identification model's finite degrees of freedom. When the selected SHM methodology is a direct correlation-based one, the intrinsic result of spatial quantization is a direct reduction in the hypothetical damage database size.

For example, consider the illustration shown in Figure 1. Notice the actual structure is prescribed to have 7 elements and the identification model, used to generate all of the potential damage scenarios, has only 2 elements. Even though the real structure could be damaged in any of the 7 elements, using only a 2 element identification model means that there are only two possible localization outcomes. That is to say that spatial quantization reduces the size of the database matrix of hypothesis damage vectors, but also reduces the accuracy of the localization. Hence, the question is the study is; by how much is the localization accuracy compromised due to spatial quantization?

Aside from this study, there are practical implications to this question as well. In practice it can be time consuming to develop extremely refined finite element models of large civil structures. (Such an occurrence might be plausible for stress analysis, however often only portions of the structure are modeled for this purpose.) Even if such a large numerical model was developed, it is not likely that its dynamic behavior would match that of the actual structure's beyond the first or second mode. A complete modal survey of the actual structure would need to be conducted in order to update, or tune, the identification model's

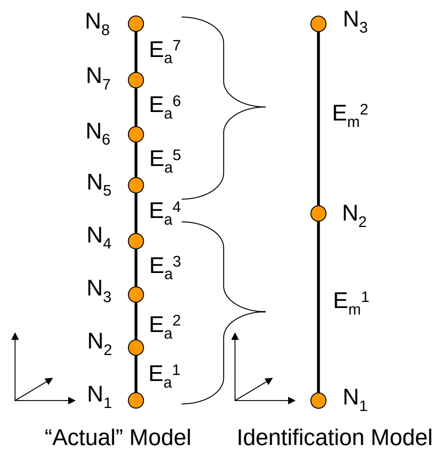


Figure 1: Spatial Quantization

modal characteristics. Moreover, creating the required database of modal characteristics for each damage scenario simulated would again prove to be too computationally intensive. As such, to be practical it makes sense to evaluate the effectiveness of the DLAC localization technique using a coarse, or reduced, damage identification model.

Damage Location Assurance Criterion

The DLAC metric is a measure of correlation between a vector of experimental natural frequency change ratios with a vector of analytical natural frequency change ratios, cf. Equation 1.

$$DLAC_j = \frac{(\{\Delta\omega\} \bullet \{\delta\omega_j\})^2}{|\{\Delta\omega\}|^2|\{\delta\omega_j\}|^2} \tag{1}$$

where the *observed* frequency change vector is defined as

$$\{\Delta\omega\} = \{\Delta\omega_1, \Delta\omega_2, \Delta\omega_3, \ldots \Delta\omega_n\} \tag{2}$$

and the *hypothesis* frequency change vector is defined for the j^{th} location as

$$\{\delta\omega_j\} = \{\delta\omega_{1j}, \delta\omega_{2j}, \delta\omega_{3j}, \ldots \delta\omega_{nj}\} \tag{3}$$

hence, $\{\Delta\omega\}$ and $\{\delta\omega_j\}$ are two vectors of dimension n.

It should also be noted that both $\{\Delta\omega\}$ and $\{\delta\omega_j\}$ vectors are normalized with respect to the structure's healthy frequencies, cf. Equation 4.

$$\Delta\omega_i = \frac{\omega_{i,\text{observe}} - \omega_{i,\text{health}}}{\omega_{i,\text{health}}} \tag{4}$$

Messina *et al.* (1996) noted that normalizing these features in this fashion equally weights all modes of the frequency change vector and reduces bias from higher modes.

It is important to note that Equation 1 can only be used to detect single damage occurrences, more complex methodologies must be employed to localize damage in structures suffering from multiple damages. Contursi *et al.* (1998) developed the Multiple Damage Location Assurance Criterion (MDLAC) based on the DLAC metric.

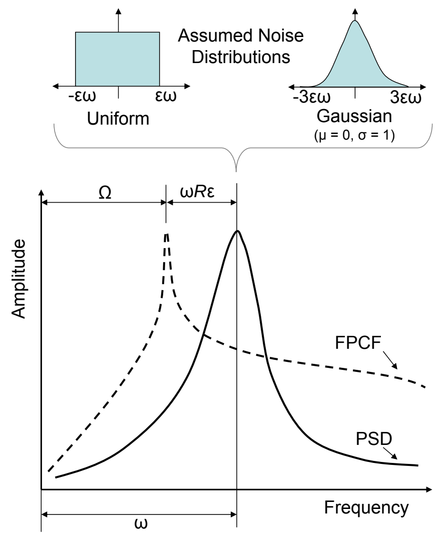


Figure 2: Errors Attributed to Automated Frequency Extraction

Simulation Noise Distribution

In this study uncertainties are introduced by seeding the analytical natural frequencies of the identification model with noise. For example, automated frequency extraction is often achieved by fitting a fractional polynomial (FPCF) to an experimental power spectral density (PSD) of the structure's response behavior. As with any curve-fitting technique there are slight errors associated with the natural frequencies extracted via FPCF and those of the actual structure, cf. Figure 2 (exaggerated). As such, when completing a numerical simulation this uncertainty can be introduced when generating the "actual" structure's natural frequencies.

Hence, for any particular natural frequency of the identification model, ω, a corresponding "actual" natural frequency of the structure, Ω, is simulated according to the following expression

$$\Omega = \omega + \omega R \epsilon \tag{5}$$

where, R is a randomly distributed number and ϵ is the percentage of imposed measurement error, as illustrated in Figure 2.

Often numerical identification models are dynamically tuned in order to facilitate accurate damage recognition and localization. For some correlation-based algorithms tuning, or updating, the numerical model is required, however the models used in this study are not updated. Moreover the number of natural frequencies (number of modes) correlated can effect the accuracy of the localization, here the frequency change vector will be limited to only four modes, i.e. $n = 4$.

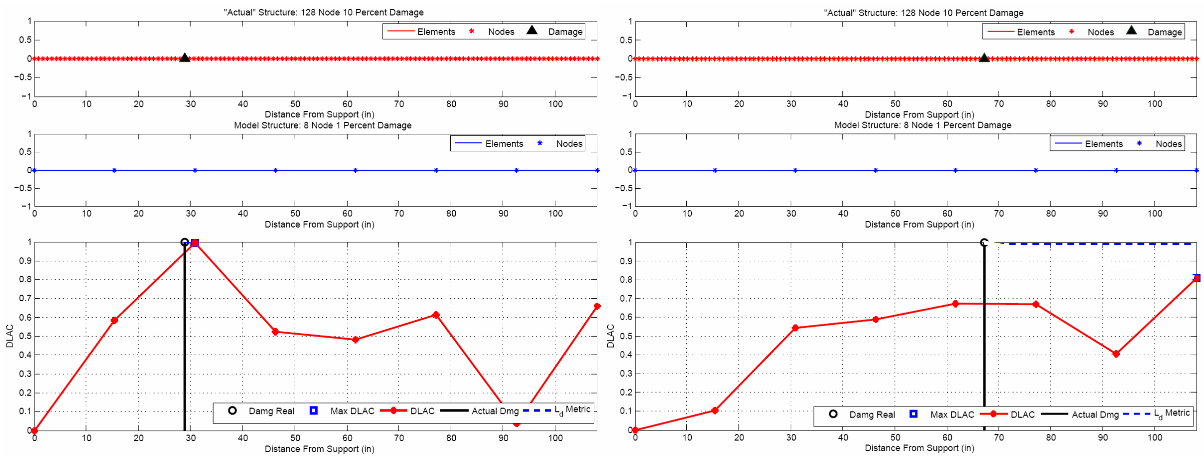
Generalized Parameters

In an attempt to generalize the results presented in this paper a few expressions are defined with respect to parameters of the "actual" model and the identification model.

Consider the model refinement metric, M, defined as,

$$\mathrm{M} = \frac{x}{y} \tag{6}$$

where, x is the number of nodes in the identification model and y is the number of nodes in the "actual" model.



a.) b.)

Figure 3: a.) Good Localization, b.) Poor Localization

A damage intensity metric, D, would also be useful and is defined as,

$$\mathrm{D} = \frac{p}{q} \tag{7}$$

where, p is the percent of damage simulated in the identification model and q is the percent of damage imposed to the "actual" model.

Note that cases of M > 1.0 are not considered in this study. It is unrealistic for an identification model to be more "refined" than that of the actual structure.

Typical DLAC Correlation Behavior

The DLAC correlation localization procedure is subject to error, cf. Figure 3a,b. The lower plot in Figure 3a,b is the DLAC correlation metric. As this value tends towards unity the location of damage is said to be localized. However, the solid black vertical bar indicates the true imposed damage location. In Figure 3a the horizontal distance between the maximum DLAC value and the imposed damage location (or L_d distance) is small indicating good localization. Conversely, in Figure 3b the L_d distance is large indicating poor localization. In both the "good" and "poor" localization example cases presented the analysis implemented an "actual" structure consisting of 127 elements (10 percent damage) and an identification model of only 7 elements (1 percent damage), e.g. M = .0625, D = 0.1.

For this study the reliability of the DLAC metric is assessed using various sized hypothesis damage databases. As such, a prescribed maximum threshold for L_d was set as 2.5 percent of the entire beam length. Any damage scenario test which yielded an L_d value of less than or equal to this value was deemed to be a successful damage localization.

Results

A 108 x 3 x .25 inch slender steel (E $=$ 30,000 ksi and $\rho = 15.23$ lbm/ft^3) cantilever beam was analyzed for this work. All results presented herein implement an "actual" structure with 128 nodes (127 Euler-Bernoulli finite elements) and an imposed damage magnitude of 10 percent. The identification model size and damage magnitude are varied. In this paper damage is simulated by adding a lumped mass to a particular node of the FE model, and "10 percent damage" corresponds to a mass equivalent to 10 percent of the total beam mass.

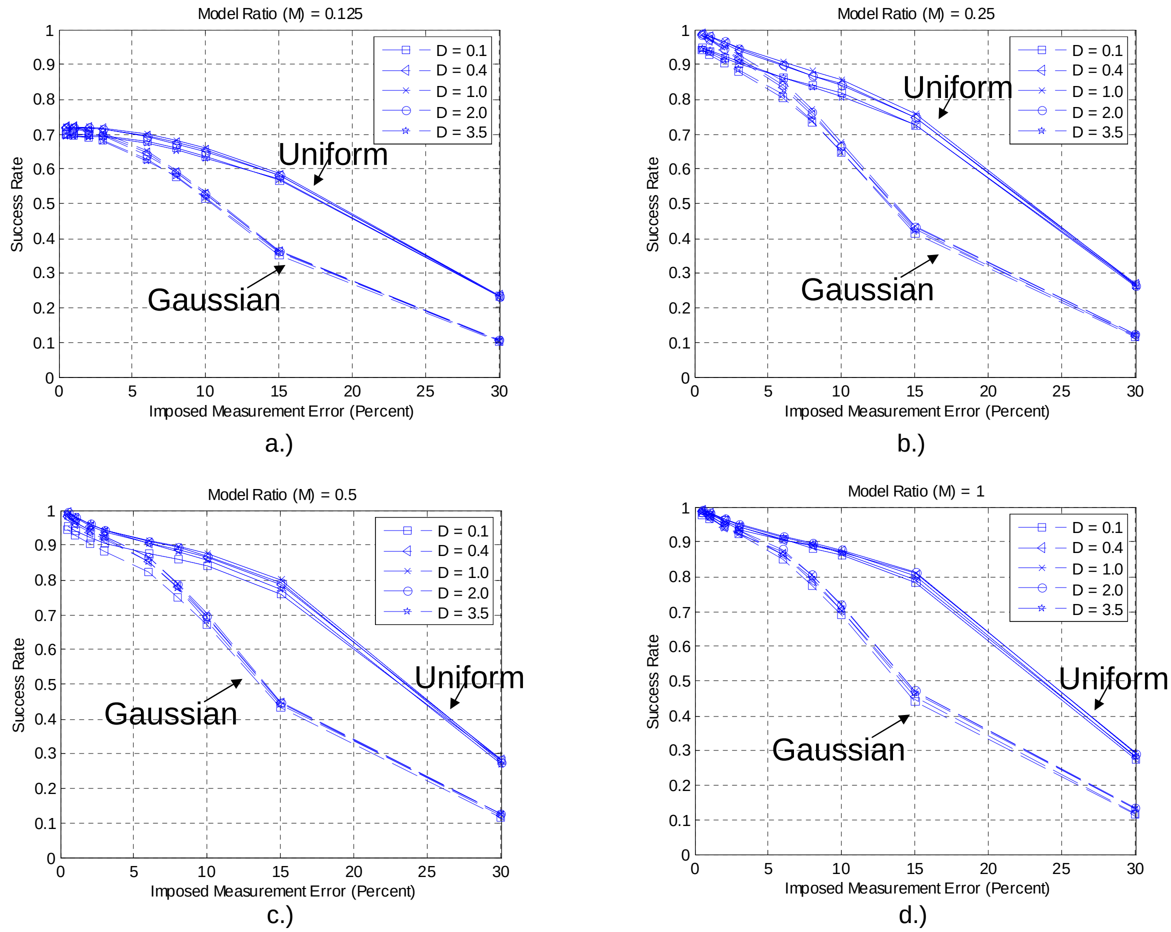


Figure 4: DLAC Quantization Performance with Noise (4 Modes)

To simulate "actual" natural frequencies, the identification model's frequencies are seeded with noise according to Equation 5. Since the distribution of errors produced by a fractional polynomial curve-fitting technique combined with other sources of error is unknown the effects of both uniform and Gaussian distributions of noise are implemented. The range of the uniform distribution is -1 to +1. The Gaussian distribution has a zero mean and standard deviation of one. Success rates were determined from 50 trials. To consistently compare results from all tests, 50 sets of 30 random numbers (for each distribution) were generated in MATLAB and stored. As such, the same random numbers were used for each different test conducted.

Notice the effect spatial quantization has on the accuracy of the DLAC localization method, cf. Figure 4. The success rate behavior for each model ratio, M, shown is similar for M = 0.25, 0.5, and 1 (Figure 4b, Figure 4c, and Figure 4d). Note that for all model ratios the damage ratio, D, has little effect on the localization outcome for this simple structure.

The drastic difference between Gaussian and uniform noise results is to be expected since the distributions were not statistically normalized with respect to each other. Yet, if the amplitude of the imposed measurement error is less than approximately 3 percent the effect of noise distribution is minimal. In all cases after this threshold is reached the noise distribution greatly effects the success rate outcome. Since actual noise characteristics are unknown perhaps a reasonable estimate of the performance of the DLAC localization metric can be found within the area enclosed by uniform and Gaussian reliability estimates.

Conclusions

The Damage Location Assurance Criterion (DLAC) methodology developed by Messina *et al.* (1996) was selected as the basis for a future distributed SHM algorithm for SWSN implementation. In an effort to reduce the hypothesis database required for the DLAC method a sensitivity analysis was performed on a simple cantilever beam considering only single damage scenarios. Despite variations with respect to noise distribution and damage magnitude the hypothesis damage database for a simple cantilever beam can be spatial quantized significantly with little reduction in localization performance. Thus, the technique is well suited for implementation on current state-of-the-art motes despite their limited system resources. Now, the next step is to embed this localization technique onto a mote and perform an online experiment in the laboratory setting.

Acknowledgements

Financial support for this investigation was provided by the United States Department of Education GAANN fellowship program and the National Science Foundation through grants CMS–0245402 and EEC–0243809. The first author would like to gratefully acknowledge the understanding and support of his family in making this work possible.

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