Off-the-Shelf Modal Analysis: Structural Health Monitoring with Motes

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NOMENCLATURE

$p(x)$, probability density function for a vector **x** belonging to $\Re^n$

V_n, volume of $\Re^n$ hypercube

k_n, number of samples within $\Re^n$

n, total number of samples

$\varphi(\mathbf{u})$, windowing function

$DLAC_j$, Damage Localization Assurance Criterion value at jth location

$\mathbf{\Delta\omega}$, vector of observed fractional frequency changes

$\mathbf{\Delta\delta_j}$, vector of hypothesized fractional frequency changes due to damage at the jth location

ω_i^h, ith healthy modal frequency

ω_i^o, ith observed modal frequency

$H(s)$, fractional polynomial

$A(s)$, denominator nth-order polynomial of $H(s)$

$B(s)$, numerator mth-order polynomial of $H(s)$

ABSTRACT

Breakthrough strides in micro-electro-mechanical systems (MEMS) demand a paradigm shift in traditional data acquisition and signal processing methodologies used for structural health monitoring (SHM). One such device which embodies MEMS technology is the Mote. Motes integrate a microprocessor, memory, and a radio transmitter together and can be outfitted with a plethora of industry standard sensory devices with little or no modification. The implication of this conglomerated setup is that it can be used to reduce, store, and ship data at the acquisition site. Moreover, the commercial development of these devices has reduced production costs and increased product development. As such, the intrinsic versatility of a Mote system can be affordably harnessed and dense sensor arrays can be utilized to enhance real-time modal parameter identification, the backbone of global vibration based SHM techniques. However there are limitations which need to be addressed. For example, significant data loss is attributed to the low bandwidth of the low power radio transmitter employed on Mica2 Motes. This issue of contention has been addressed by recent technological improvements in wireless transmission standards. Yet in spite of the progress made by new transmission protocols and standards towards reducing radio power consumption, increasing bandwidth, and reducing transmission latency, they alone will not meet all of the needs of a full-scale wireless SHM system. In light of this realization the efforts of this paper are shifted from previous studies where time histories were streamed from the data acquisition site to a central location for processing. Now instead the focus is on decentralizing the SHM system by exploiting the on-board computational faculties of a Mote. Here a simple signal processing and spectrum curve-fitting technique is used to automatically extract dominant frequency components of an acceleration time history record. Identified frequencies are then implemented in a probabilistic neural network (PNN) and correlation-based damage localization procedures in such a fashion to simulate on-board implementation of this SHM methodology on a Mote platform. This paper will document the efficacy of successful damage detection and localization experiment performed with acceleration impulse response time histories acquired from off-the-shelf Motes and sensor hardware.

INTRODUCTION

Micro-electro-mechanical systems (MEMS) are defined as, “the integration of mechanical elements, sensors, actuators, and electronics on a common silicon substrate through microfabrication technology” [1]. By bringing these essential elements into one platform complete systems-on-a-chip can be developed thereby creating smart electronic technologies that have the ability to react autonomously to the environment in which they are placed [1]. It is clear from the even this elementary description of what MEMS is that this technology has much to offer the modal analysis/system identification and health monitoring communities. Take, for example the Mote, a device embodying MEMS technology, these devices integrate a computational processor, memory, and a radio transmitter together and can be configured to be compatible with a plethora of industry standard sensory devices with little modification. It is clear that these devices, equipped with high performance sensory equipment, offer the ability to revolutionize the current state-of-art of data acquisition practices. Therefore to extort the full capacities of this technology for modal analysis and infrastructural health monitoring a paradigm shift in data acquisition and processing methodologies is requisite.

The commercial development of such devices as the Mica series Mote by CrossBow® Technology has reduced production costs and increased the development of the Mote platform making these systems an attractive research topic in networked data acquisition and distributed data processing. As such, researchers in computer science, electrical, and civil engineering have come together to develop smart Wireless Sensor Network (WSN) for Structural Health Monitoring (SHM). Since the inception of a WSN for SHM many researchers have invested their resources on developing better low power, high resolution sensing devices paramount to the practical implementation of a practical health monitoring technology [2,3,4]. Others have focused on networked data acquisition schemes and increasing the computational power of the smart sensor [5,6,7,8]. And a few have focused on developing SHM algorithms to embed in a WSN [2,7,8,9]. The efforts presented here are focused on integrating a SHM algorithm and WSN together for direct implementation.

BACKGROUND

Recent studies with Mica generation Motes indicate that complete time history records can be transmitted wirelessly at sampling rates sufficient for accurate spectrum characterization of civil structures. Xu *et al.* (2004) focused on reliably acquiring and transmitting structural response time histories with Mica2 motes and a custom built high quality “vibration card” [5]. To mitigate data losses intrinsic of wireless transmissions, retransmission and compression schemes were investigated in this study. The result was the development of a wireless structural data extraction network named Wisden, a system which is suitable for centralized data processing. To validate the work a ten mote system was deployed on a ceiling truss structure and 20 seconds of response time history were recorded then transmitted to a central base station within a five minute period. No consideration was given to parameter identification, damage detection or localization. A study by Caffrey *et al.* (2004) implementing the Wisden system did focus on the interplay between networked sensing and structural health monitoring with consideration given to a networked damage detection algorithm through simulation [10].

Clayton *et al.* (2005) instrumented a cantilever beam with four Mica2 motes and performed a damage localization experiment. Here unsynchronized impulse response time histories streamed directly from the test structure at 100 Hz to a central computer for post-processing [11]. Several test cases were considered where structural damage was simulated by perturbing the mass of the system. Despite transmission data losses primarily due to the Mica2 Mote’s limited radio bandwidth, a correlation-based damage localization procedure was successfully implemented with unmodified mote hardware and off-the-shelf multi-sensor boards. Damage was located in three test configurations. A brief study was performed documenting the effects of bandwidth contention verses the number of motes streaming data at various sampling rates under Carrier Sense Multiple Access-Collision Avoidance (CSMA-CA) transmission protocol rules.

Paek *et al.* (2005) continued the Wisden system research and development. For this study modifications were made to the Wisden system which included increasing the sampling frequency from 50 Hz to 200 Hz and modifying the data compression scheme to prevent unintended filtering [6]. Mica2 motes were replaced with newer MicaZ motes which incorporate the ZigBee (IEEE 802.15.4) radio technology. Marketed as low power alternative to the BlueTooth specification, the Zigbee specification offers a nominal theoretical bandwidth of more than 12 times that of Mica2 generation radios. The same ceiling truss model was used as the experimental test bed and the modified Wisden system was integrated onto a 14 mote system. A 40 second response time history was recorded and transmitted to a central base station within a five minute period. A validation experiment was performed and good agreement was found between structural response data gathered from a Wisden sensor node and a traditional wired sensor in both the time and frequency domains. This study concluded with a side-by-side performance evaluation of Mica2 and MicaZ motes. By simply implementing the MicaZ mote platform both transmission latency and data loss were minimized due to the enhanced radio bandwidth.

Even with advancements in low power wireless transmission protocols, better radios will not address all of the demands of a wireless sensor network for health monitoring. If the focus is placed solely on transmission protocols then available bandwidth, data loss, and latency will continue to plague a WSN as the number of networked devices increases. This in turn defeats one of the most advantageous benefits for developing such a system for SHM, increased sample point coverage achieved by creating dense arrays of sensor networks. Moreover, networking schemes that are developed around a centralized data processing scheme also prohibit sample point coverage growth since there is maximum threshold to the amount of data that can be stored and processed at one location. From these arguments it can be said that transmitting full length time histories to one centralized location does not lend itself well to WSN for SHM. In response to the constraints placed on data transmission, storage, and processing this work focuses on a distributed-process substructured WSN for SHM and concludes with experimental validation of a distributed health monitoring algorithm using test data gathered by unmodified off-the-shelf Motes.

The concept of developing a data acquisition system in collaboration with the health monitoring methodology is logical and was suggested in 2001 by Farrar and Sohn [12]. Lynch *et al.* (2004) went on to lay out the framework of a integrated WSN for SHM implementing custom built wireless sensor platforms that could calculate on-board auto-regressive moving average (ARMA) model coefficients [8]. In Figure 1, the authors of this work suggest their WSN paradigm for SHM.

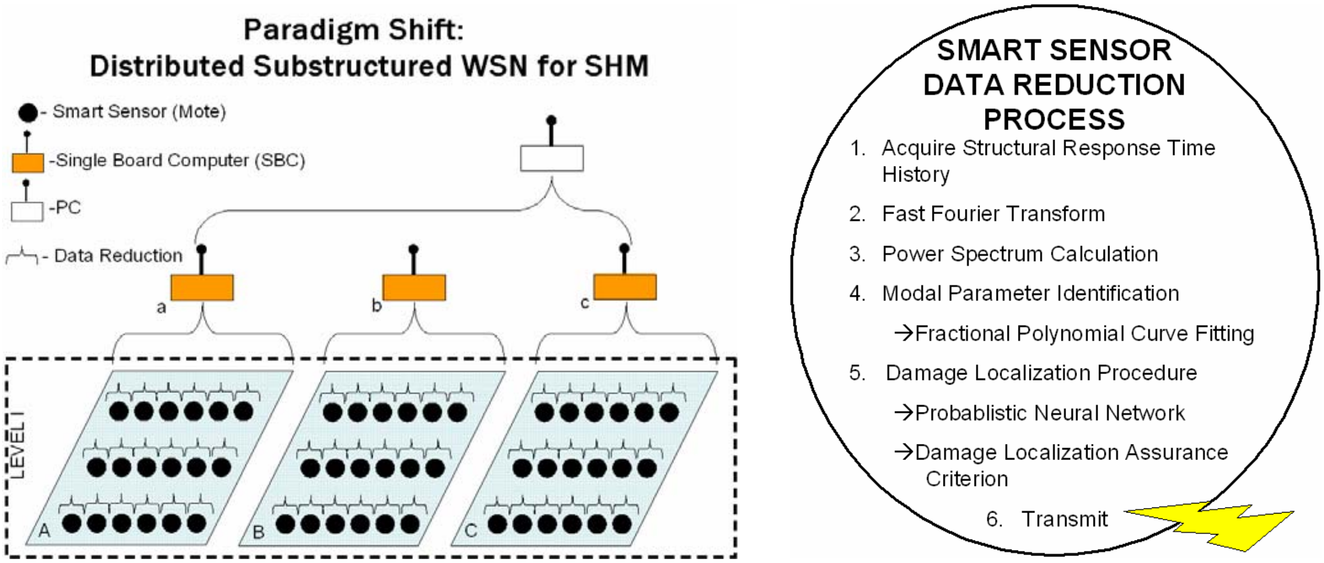


Figure 1: A Distributed and Substructured Wireless Sensor Network for Structural Health Monitoring. Level I of this WSN paradigm for SHM relates to data reduction at the acquisition site.

The focus of this work is placed on what occurs within the "Level I" dashed rectangle of Figure 1. Level I includes acquiring data from the structure and processing it before transmission. Implementation of a damage localization procedure at the sensor level automatically alleviates the need for a data compression scheme because data is reduced during the localization computation. Two such damage localization procedures have been found to work well with the decentralization concept and are applied in this study.

HARDWARE AND SOFTWARE

MicaZ Motes, manufactured by CrossBow® Technology, are equipped with a 16-channel Chipcon CC2420 radio, a 7.3827 MHz Atmel ATmega 128 microcontroller, 128 KB of program memory, 4 KB of data memory, and 512 KB of external flash memory [13]. The radio operates in the unlicensed 2.4 to 2.4835 GHz band and is compatible with the IEEE 802.15.4 standard. It offers a maximum theoretical bandwidth of 250 kilobits per second. The MicaZ Mote interfaces with external sensing devices through a 51-pin expansion connector which contains a 10-bit analog-to-digital converter (ADC) to quantize analog signals produced by sensors. A MIB510CA Interface Board can also utilize the expansion connector to link a Mote to a PC via serial interface, whereby programs may be uploaded to or data downloaded from a Mote.

To acquire structural response time histories a MTS310CA Multi-Sensor Module was connected to the Mote. This module contains several other sensing devices in addition to the accelerometer used in this study. The accelerometer, a dual axis ADXL202JE, is rated to produce accurate readings at ±2g with a 2 mg resolution and has a 1000g shock survival [14]. The low sensitivity of the ADXL202 accelerometer and the low resolution of the Mica series Mote's 10-bit ADC does make this acquisition device less than optimal for dynamic testing [2,4]. However, in spite of these hardware limitations the structure was sufficiently excited during testing in this study and useful response data could be recorded.

The Motes ran TinyOS, an open-source operating system which was developed at UC-Berkeley for wireless embedded sensor networks [15]. TinyOS comes with a library of built-in applications, including an oscilloscope application which provided the basis for the data acquisition software designed and implemented for this study. In this study all the Motes form a single-hop wireless network. Data acquired from various Motes was synchronized and transmitted to a base station in real time. As such, data loss due to contention of the wireless link was presumed to be a serious issue as it was in a previous study conducted by the authors implementing Mica2 Mote platforms [11]. To circumvent this problem a staggered transmission schedule known as Time Division Multiple Access (TDMA) was implemented on top of the default Medium Access Control protocol (B-MAC) provided by the TinyOS operating system [16].

Motes were configured to sample the accelerometer in a synchronized manner at a user-defined frequency. After a Mote collected 10 samples, it subsequently sent a message with the data back to a Mote connected to a laptop computer, used as the base station, in accordance to its TDMA time slot. Time slots are assigned during the network configuration and are based on the number of Motes acquiring data. The application divides the time between each expected message from a Mote, the same as the time to collect 10 samples, into 10 equal slots and assigns each Mote a unique transmission slot, while maximizing the amount of time between successive transmissions from different Motes. This increases the reliability of data transfer as a Mote does not contend with others for the wireless link while transmitting. This mechanism is beneficial because data messages are not acknowledged nor retransmitted in this system. While data acquisition is underway, the user can monitor the data being acquired and data loss statistics in real time on the laptop computer.

DAMAGE LOCALIZATION TECHNIQUES

Probabilistic Neural Network (PNN)

Among previous studies on pattern classification methods applied to structural damage identification, many studies treated the supervised learning under the assumption that the forms of the underlying density functions were known. For instance, Vanik *et al.* (2000) assumed the probability density function to have the form of a Gaussian distribution [17]. However, in practical pattern classification problems for structural damage identification this assumption is doubtful. Especially for damage location identification, it is difficult to estimate the density function of a damage location to have a precise form. This study attempts to circumvent this dilemma by applying a nonparametric technique that can be used with arbitrary distributions and without the assumption that the forms of the underlying densities are known.

The basic idea of a nonparametric technique is simple. It relies on the fact that the probability density $p(\mathbf{x})$ for a vector $\mathbf{x}$ in a region $\Re$ is given by

$$p(x) = \frac{k_n / n}{V_n} \tag{1}$$

whereby three conditions are required:

$$\begin{aligned} \lim_{n\to\infty} V_n &= 0 \\ \lim_{n\to\infty} k_n &= \infty \\ \lim_{n\to\infty} k_n / n &= 0 \end{aligned} \tag{2}$$

Here, V_n is the volume of R_n, k_n the number of samples falling in R_n, and n the total number of samples.

There are two common ways of obtaining sequences of regions that satisfy these conditions listed in Equation (2). One way is to shrink an initial region by specifying the volume V_n as some function of n, such as $V_n = 1/\sqrt{n}$. This is referred to as the Parzen-window method. The second method is to specify k_n as some function of n, such as $k_n = \sqrt{n}$. This is the k_n-nearest-neighbour estimate method [18].

The Parzen-window approach to estimate probability densities can be introduced by temporarily assuming that the region $\Re_n$ is a d-dimensional hypercube whose volume is given by

$$V_n = h_n^d \tag{3}$$

where h_n is the length of an edge of that hypercube. We can obtain an analytic expression for k_n, the number of samples falling in the hypercube, by defining the following window function:

$$\varphi(\mathbf{u}) = \begin{cases} 1 & \left|u_j\right| \le 1/2 \qquad j = 1,\ldots,d \\ 0 & otherwise \end{cases} \tag{4}$$

Thus, $\varphi(\mathbf{u})$ defines a unit hypercube centered at the origin. It follows that $\varphi((\mathbf{x}-\mathbf{x}_i)/h_n)$ is equal to unity if $\mathbf{x}_i$ falls within the hypercube of volume V_n centered at $\mathbf{x}$, and is zero otherwise. The number of samples in this hypercube is therefore given by

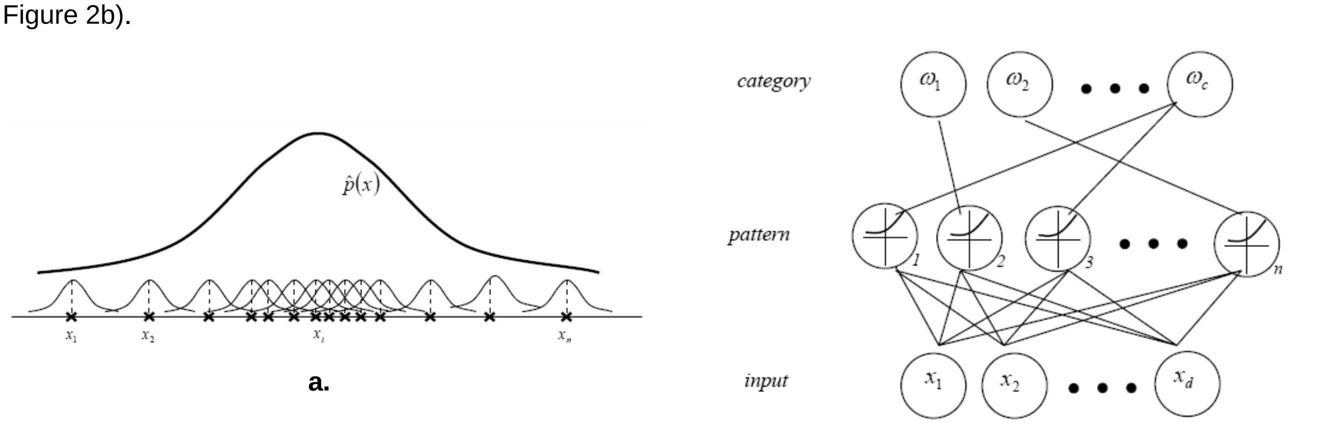
$$k_n = \sum_{i=1}^{n} \varphi\left(\frac{\mathbf{x}-\mathbf{x}_i}{h_n}\right) \tag{5}$$

and, when we substitute this into Equation (1) we obtain the estimate

$$p_n(\mathbf{x}) = \frac{1}{n}\sum_{i=1}^{n} \frac{1}{V_n}\varphi\left(\frac{\mathbf{x}-\mathbf{x}_i}{h_n}\right) \tag{6}$$

In essence, the window function is being used for interpolation---each sample contributing to the estimate in accordance with its distance from $\mathbf{x}$ shown as Figure 2a.

The Parzen-window approach can be implemented as a neural network known as a Probabilistic Neural Network (PNN) [18]. Suppose it is desired to form a Parzen estimate based on n patterns, each of which is d-dimensional, randomly sampled from c classes. The PNN for this case consists of d input units comprising the input layer, where each unit is connected to each of the n pattern units; each pattern unit is, in turn, connected to one and only one of the c category units. The connections from the input to pattern units represent modifiable weights, which will be trained. Each category unit computes the sum of the pattern units connected to it (c.f. Figure 2b).



a. **b.**

Figure 2: a.) Each Sample Contributing to the Estimate, b.) Probability Neural Network Architecture.

Correlation-based Damage Localization

The basis of the correlation technique described here is the inner product of two vectors of resonant frequencies. One vector consists of hypothesis modal frequencies determined from a numerical model of the structure with damage at a unique location. A suite, or database, of such synthesized vectors is compiled for each unique damage location. Then, a vector of observed frequencies is obtained from the structure and the inner product the observed frequency vector with each of the data-based hypothesis vectors is performed. It follows that when the hypothesized vector accurately represents the true damage state of the structure the vector would be collinear with the observed vector and the cosine of the angle between them would tend to unity.

The Damage Location Assurance Criterion (DLAC) correlation method developed by Mesina *et al*. (1996) is of a similar form and is presented below as Equation (7) [19].

$$\mathrm{DLAC_j} = \frac{\left(\{\Delta\omega\}^{\mathrm{T}}\{\delta\omega_j\}\right)^2}{\left(\{\Delta\omega\}^{\mathrm{T}}\{\Delta\omega\}\right)\left(\{\delta\omega_j\}^{\mathrm{T}}\{\delta\omega_j\}\right)} \tag{7}$$

where, $\mathbf{\Delta\omega}$ represents a vector of the first ith identified fractional frequency changes observed. Each component of $\mathbf{\Delta\omega}$ can be written as follows

$$\Delta\omega_i = \frac{\omega_i^h - \omega_i^o}{\omega_i^h} \tag{8}$$

Where, ω_i^h represents the natural frequency of the ith mode determined when the structure is deemed “healthy” and ω_i^o denotes the ith natural frequency of the monitored (observed) mode. Note that each component of $\Delta\omega$ is normalized with respect to a healthy modal frequency to reduce bias introduced from more sensitive higher modes. Likewise, a suite of fractional hypothesis damage vectors, $\delta\omega_j$, simulating damage at the jth location of the structure is synthesized from a finite element model. A DLAC value of 1.0 indicates an exact correlation of the observed fractional frequency change vector, $\Delta\omega$, with one particular hypothesis damage vector, $\delta\omega_j$, thus localizing the damage to the jth location. Conversely, a DLAC value tending to zero indicates little correlation with any particular damage scenario. It is important to note that Equation (7) can only be used to detect single damage occurrences. Multiple damage instances can be evaluated in a similar fashion to the DLAC scheme using the Multiple Damage Localization Assurance Criterion (MDLAC) developed by Contursi *et al.* (1998) [20].

RESONANT FREQUENCY IDENTIFICATION

It is important to note that both the PNN and correlation-based SHM approaches discussed within the previous section rely on the observation of natural frequency changes to detect and localize damage, thus accurate frequency characterization of the healthy and damaged structure is paramount. In theory to implement either of these methods on-board a Mote system there is a need for automated characterization of the dominant frequency components of a structural response time history. When a centralized sensor array is implemented automated frequency identification can be carried out with the Eigensystem Realization Algorithm (ERA) develop by Juang and Papa (1985) [21]. However for a distributed sensor array, multiple channels of response data are not assumed to be available at each sensor node unless one reverts back to transmitting time histories between Motes. ERA requires several channels of data to be processed at one time in order to differentiate between actual structural resonances and spurious mathematical modes. That is to say for a decentralized system the traditional ERA modal identification procedure is not effective. As such, to act in accordance with the constraints of a decentralized system, an automated spectrum curve-fitting technique was tested.

The spectrum curve-fitting technique investigated in this study implements a fractional polynomial, *H(s)*, and is presented in Equation (9) [22]. It is readily observed that *H(s)* consists of an m^{th}-degree numerator polynomial *B(s)* and n^{th}-degree denominator polynomial *A(s)*.

$$H(s)=\frac{B(s)}{A(s)}=\frac{b_1 s^m + b_2 s^{m-1} + \ldots + b_{m+1}}{a_1 s^n + a_2{}^{n-1} + \ldots + a_{n+1}} \tag{9}$$

The order of *A(s)* is proportional to the number of singularities, or resonant frequencies, to be captured by *H(s)*. Similarly, *B(s)* relates to the number of zeros, anti-resonances, to be captured by *H(s)*. The roots of *A(s)* are complex conjugate pairs that have imaginary parts corresponding to natural frequencies of the system. A controls viewpoint could be adopted in order to determine the order of *A(s)* and *B(s)*. A novel and straightforward numerical solution for evaluating the unknown coefficients of *B(s)* and *A(s)* was presented by Levy (1959) therefore it is reasonable to assume this method can be implemented on existing Motes [23].

An empirical study indicated that all of the modes of the experimental system tested in this study could be identified using the Fractional Polynomial Curve-fitting (FPCF) technique. To ensure reliable characterization of resonant frequencies, three fractional polynomials were defined over three unique frequency bands. As such, fractional polynomials were fit to the test data over a low, mid, and high frequency band for each experiment. Figure 3 illustrates graphically the accuracy of the FPCF technique discussed here.

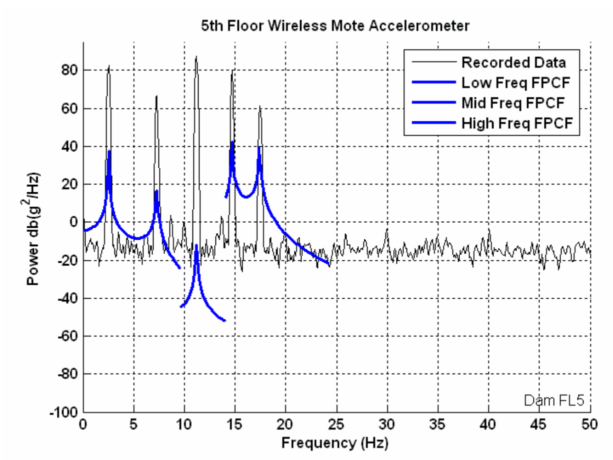


Figure 3: Experimental Power Spectrum with Fractional Polynomial Curve-fitting

A numerical model of the structure is needed for both localization techniques presented in this investigation, therefore it is sensible to infer that the approximate modal frequencies of the actual structure. Thus rational estimates for the frequency bands over which to specify *H(s)* functions can be made. It should also be noted that the piecewise FPCF scheme presented here performed robustly to frequency shifts incurred by damages. Healthy frequency band limits specified for *H(s)* remained the same for all tested damage scenarios.

DAMAGE LOCALIZATION EXPERIMENT

To validate the data acquisition performance of off-the-shelf MicaZ Motes and sensor hardware for damage detection and localization a laboratory experiment was conducted. In this study a five bay lumped mass shear building model was selected as the test structure, c.f. Figure 4a. MicaZ Motes were installed on floors 1, 2, 4 and 5 of the building, c.f. Figure 4b, and were configured in such a fashion as to record accelerations in the global x-direction. In this study damage was induced to the structure by reducing the inter-storey column stiffness. This stiffness reduction was facilitated by exchanging the original columns by those with a lesser moment of inertia, c.f.

Figure 4d. By replacing two of the original four inter-story columns with columns of a lesser moment of inertia the cumulative inter-storey stiffness was reduced by 33 percent, c.f. Figure 4e. To excite the structure for testing an impulse load was generated along the global x-axis by striking the 4th floor of the structure with a modally tuned impact hammer. Test records were recorded for single damage cases.

Data was not processed or stored on-board the Motes for this study. Instead synchronized time histories of response data were streamed directly from all four motes simultaneously to a base station and stored on a PC using the TDMA protocol previously described. To establish a basis for comparison in this study wired acceleration records were also logged at each floor simultaneously during testing.

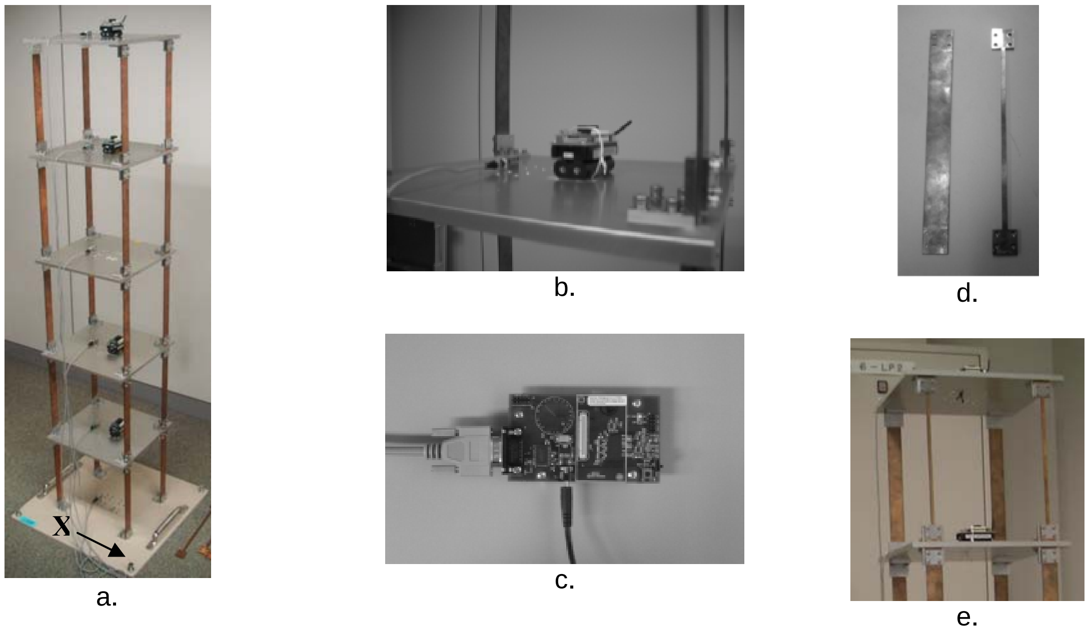


Figure 4: Experimental Setup: a.) Instrumented Model Structure, b.) MicaZ Mote, c.) Mote Base-station Receiver, d.) Healthy and Damaged Column, e.) Damaged Columns Installed

DAMAGE LOCALIZATION SIMULATION RESULTS

Wired and wireless acceleration impulse response time histories were acquired simultaneously during experimentation. Time histories were then post-processed on a PC to identify the resonant frequencies of the test structure. A direct comparison between frequencies identified by manual spectrum peak picking, the Eigensystem Realization Algorithm (ERA) and Fractional Polynomial Curve-fitting (FPCF) is shown with good agreement in Table 1.

Table 1: Experimentally Identified Resonant Frequencies

Identfied Resonant Frequencies *Wired Accerometer Data*						Identfied Resonant Frequencies *Wireless Accerometer Data*					
HEALTHY	*mode I*	*mode II*	*mode III*	*mode IV*	*mode V*	**HEALTHY**	*mode I*	*mode II*	*mode III*	*mode IV*	*mode V*
Manual	2.64	7.72	12.30	15.82	18.26	*Manual*	2.54	7.52	12.01	15.53	17.77
ERA	2.59	7.71	12.33	15.86	18.21	*ERA*	2.52	7.51	12.02	15.46	17.75
FPCF	2.60	7.72	12.33	15.87	18.22	*FPCF*	2.52	7.53	12.03	15.48	17.77
Damg FL1	*mode I*	*mode II*	*mode III*	*mode IV*	*mode V*	**Damg FL1**	*mode I*	*mode II*	*mode III*	*mode IV*	*mode V*
Manual	2.34	7.23	11.91	15.62	18.16	*Manual*	2.34	7.03	11.72	15.33	17.68
ERA	2.37	7.23	11.95	15.66	18.17	*ERA*	2.30	7.04	11.65	15.27	17.72
FPCF	2.37	7.23	11.94	15.67	18.16	*FPCF*	2.31	7.05	11.66	15.29	17.73
Damg FL2	*mode I*	*mode II*	*mode III*	*mode IV*	*mode V*	**Damg FL2**	*mode I*	*mode II*	*mode III*	*mode IV*	*mode V*
Manual	2.44	7.72	11.91	14.84	17.97	*Manual*	2.34	7.52	11.62	14.45	17.48
ERA	2.41	7.74	11.89	14.85	17.92	*ERA*	2.35	7.55	11.60	14.49	17.49
FPCF	2.43	7.74	12.28	14.85	17.94	*FPCF*	2.35	7.55	11.60	14.49	17.49
Damg FL3	*mode I*	*mode II*	*mode III*	*mode IV*	*mode V*	**Damg FL3**	*mode I*	*mode II*	*mode III*	*mode IV*	*mode V*
Manual	2.44	7.52	11.72	15.62	17.48	*Manual*	2.44	7.32	11.43	15.23	16.99
ERA	2.48	7.50	11.70	15.63	17.45	*ERA*	2.41	7.30	11.40	15.22	17.02
FPCF	2.49	7.52	11.71	15.65	17.48	*FPCF*	2.44	7.30	11.43	15.59	17.02
Damg FL4	*mode I*	*mode II*	*mode III*	*mode IV*	*mode V*	**Damg FL4**	*mode I*	*mode II*	*mode III*	*mode IV*	*mode V*
Manual	2.54	7.13	12.21	15.53	17.38	*Manual*	2.44	6.93	11.91	15.14	16.99
ERA	2.54	7.12	12.18	15.47	17.38	*ERA*	2.45	6.91	11.85	15.05	16.90
FPCF	2.55	7.13	12.20	15.49	17.38	*FPCF*	2.48	6.95	11.89	15.10	16.96
Damg FL5	*mode I*	*mode II*	*mode III*	*mode IV*	*mode V*	**Damg FL5**	*mode I*	*mode II*	*mode III*	*mode IV*	*mode V*
Manual	2.64	7.52	11.52	15.14	17.97	*Manual*	2.54	7.32	11.23	14.75	17.48
ERA	2.60	7.46	11.48	15.09	17.91	*ERA*	2.51	7.25	11.17	14.67	17.42
FPCF	2.62	7.48	11.50	15.12	17.91	*FPCF*	2.53	7.28	11.20	14.72	17.41

The identified frequencies were then utilized in the PNN and correlation-based damage localization methodologies, c.f. Figure 5 and 6. Though the PNN approach yields more distinct damage location indicators, damage in each storey was clearly localized by both methods.

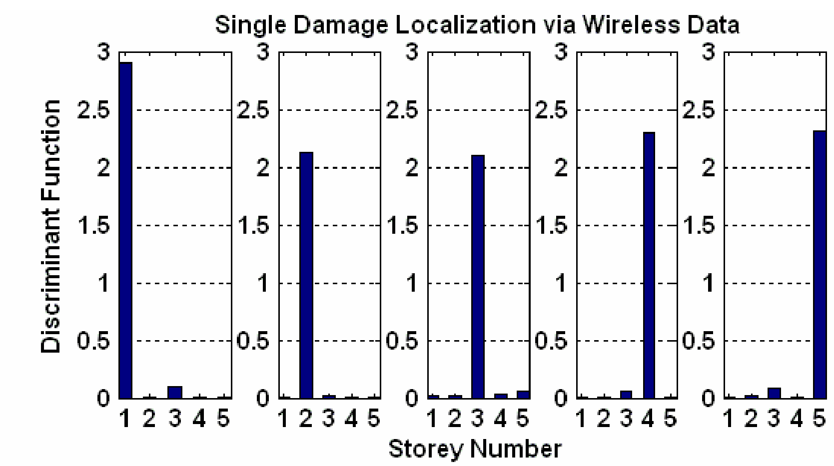


Figure 5: Parzen Window Neural Network Localization Scheme

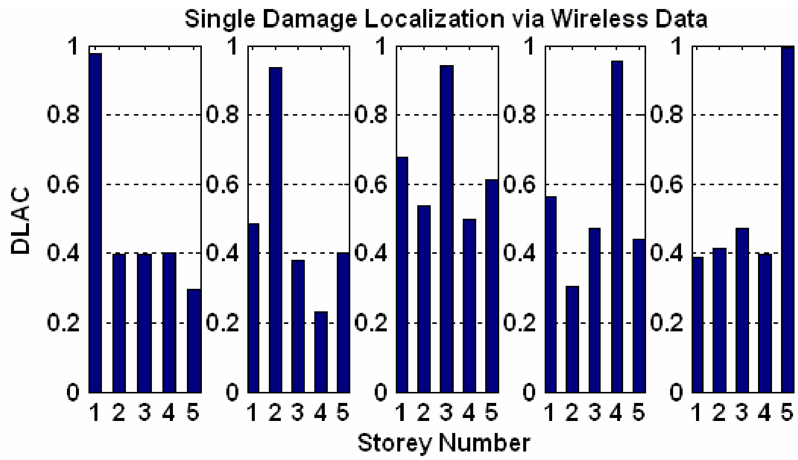


Figure 6: Correlation-based Localization Scheme

CONCLUSION

Despite significant strides made in developing wireless smart sensor networks, the integration of these powerful systems with adjudicatory structural health monitoring (SHM) technologies has not yet been fully achieved. In order to facilitate the development of such a networked monitoring scheme a damage localization experiment was conducted implementing off-the-shelf wireless sensing devices called Motes. Experimental impulse response functions were gathered with the Motes and were processed offline in a manner to simulate a distributed data processing system. The efficacies of two SHM techniques adapted for a distributed, substructured WSN paradigm were shown to be effective.

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