

Automated Modal Parameter Estimation by Parallel Processing within Wireless Monitoring Systems

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Abstract: With recent advances in low-cost wireless sensing and data acquisition technology, it has become feasible to instrument a large structure with a dense array of wireless sensors. Furthermore, analog-to-digital conversion and data processing capabilities of current wireless sensor prototypes offer the ability to efficiently distribute data processing tasks across a large network of wireless sensing nodes. For decades, the structural engineering community has been adapting input-output modal identification techniques for use in large-scale civil structures. However, unlike in mechanical or aerospace engineering, it is often difficult to excite a large civil structure in a controlled manner. Thus, additional emphasis has been placed on developing a number of output-only modal identification methods for use in structural engineering applications. In this paper, three of these output-only methods (peak picking, random decrement, and frequency domain decomposition) are modified for implementation in a distributed array of processors embedded within a network of wireless sensor prototypes. The software architecture proposed emphasizes parallel data processing and minimal communication so as to ensure scalability and power efficiency. Using the balcony of a historic theater in metropolitan Detroit as a testbed, this network of wireless sensors is allowed to collect and process acceleration response data during a set of vibration tests. The embedded algorithms proposed in this study are used to autonomously determine the balcony's modal properties with network-derived results found to be comparable to those derived from traditional offline techniques.

DOI: 10.1061/(ASCE)1076-0342(2008)14:1(102)

CE Database subject headings: Automation; Estimation; Monitoring; Data collection; Sensors; Structural engineering; Modal analysis.

Introduction

Wireless sensor networks (WSNs) offer a great number of benefits to the structural engineering community. Primarily, wireless sensing technologies promise to drastically improve the engineer's ability to monitor the structural integrity of a bridge, building, tunnel, or other complex civil structure in real time. This type of continuous health monitoring is important because it can greatly reduce routine maintenance and inspection costs, while providing an increased level of public safety by alerting engineers to potential structural problems before failure occurs. While networks of tethered sensors have already been installed in large

structures around the world (Hippley 2001; Wu 2003; Ko and Ni 2005), the high costs associated with traditional tethered monitoring systems have prevented their widespread adoption. By eliminating the need for the extensive lengths of cable required to link sensors to a central data repository, wireless sensing technologies can be deployed at both reduced costs and with higher nodal densities than traditional tethered monitoring systems that incur costs on the order of a few thousand dollars per sensing channel (Celebi 2002). In addition to the cost savings derived from wireless communication, wireless sensors also integrate analog-to-digital converters (ADCs) and low-power microprocessors. In particular, microcontrollers collocated with the sensor can be leveraged to perform data processing tasks at each sensing node. Today, a wide variety of commercial and academic wireless sensor prototypes have been developed and validated (Lynch and Loh 2006).

The ability of wireless sensors to autonomously collect and analyze data has led to these devices being labeled as "smart" sensors (Spencer et al. 2004). By locally interrogating data at the individual sensing node, such "smart" devices can offer several distinct improvements to traditional monitoring methods. Primarily, instead of having to transmit long records of raw time history data from each node to a central processing station, a "smart" system only needs to transmit locally processed data, which is typically only a fraction of the size of raw time history data. By limiting the amount of communication necessary within a sensing network, power consumption and network bandwidth problems traditionally associated with wireless transmission can be greatly mitigated (Lynch et al. 2004). Furthermore, by maximizing power efficiency and leveraging efficient bandwidth utilization, wireless

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Note. Discussion open until August 1, 2008. Separate discussions must be submitted for individual papers. To extend the closing date by one month, a written request must be filed with the ASCE Managing Editor. The manuscript for this paper was submitted for review and possible publication on May 17, 2007; approved on September 18, 2007. This paper is part of the *Journal of Infrastructure Systems*, Vol. 14, No. 1, March 1, 2008. ©ASCE, ISSN 1076-0342/2008/1-102-113/\$25.00.

monitoring systems can be made highly scalable (i.e., defined by high nodal counts).

Numerous researchers have used embedded engineering algorithms such as autoregressive model fitting, wavelet transforms, and fast Fourier transforms within the computational core of a network of wireless sensors (Lynch 2007). These algorithms have typically been performed independently at the sensor, without direct sharing of data between nodes. As a result, spatial information is only obtained at the central data repository where data processed by the wireless nodes is collected. For example, a recent instrumentation of a 14-node wireless monitoring system installed on a concrete box girder bridge illustrated mode shape estimation by peak picking. In the system, wireless sensors communicate the imaginary component of the Fourier spectrum at modal peaks to a central data repository where the mode shapes are assembled (Lynch et al. 2006). But because wireless devices can be deployed in ad-hoc networks featuring peer-to-peer communication, many analytical routines can be easily decentralized and distributed across a large number of wireless nodes with individual processing capabilities. By employing parallel processing techniques, an ad-hoc wireless sensing network can obtain spatial information without the need for a central data repository. As a result, researchers have begun to look at various parallel processing techniques for distributed data processing on wireless sensing networks. Chintalapudi et al. (2006) present a tiered system where data processing tasks can be performed on a distributed network using powerful gateway nodes. This method involves a top-down approach that allows for a flexible and highly abstracted user interface, but in which the computational capabilities of the prolific lower nodes are largely ignored. Other methods involving hierarchical sensing networks where data can be aggregated and compressed have also been presented in the literature (Gao 2005; Nagayama et al. 2006). These promising techniques can help improve network scalability by limiting data size and mitigating data loss problems through averaging, but they rely on a tradeoff between data size and accuracy. While wireless sensing technology has seen significant growth in recent years, additional work is still needed to modify existing analysis methods for parallel execution within a distributed network of wireless sensors.

The idea of identifying system parameters from dynamic response data originated 2 decades ago within the mechanical and aerospace engineering communities (Ewins 1986; Ljung 1987; Juang 1994). The subsequent development of a set of system identification techniques was fueled largely by the need for analytical tools that could be used to build effective models of dynamic physical systems from observed system data. For obvious reasons, the ability to experimentally extract system parameters from sensor data offers enormous benefits across all engineering disciplines. In civil engineering, the ability to ascertain modal information (modal frequencies, mode shapes, and damping ratios) from sensor data has paved the way for the assessment of structural performance and the calibration of analytical design models (Alampalli 2000). In some instances, modal parameters can even be used to detect and locate structural damage in the wake of natural events like earthquakes (Doebbling et al. 1998).

In the aerospace and mechanical engineering fields, modal parameter identification techniques are typically carried out using both input and output measurement data, which can be related through frequency response functions (FRFs) in the frequency domain. However, it is often difficult to excite a large civil structure in a controlled manner with measurable input excitation forces. Thus, modal parameter estimation techniques using

output-only dynamic data have become quite popular within the civil engineering field (Cunha and Caetano 2006). In order to extract meaningful system properties from a large civil structure, a large amount of data must be available from a dense array of sensors. Fortunately, recent advances in low-cost wireless sensing technologies have made the dense instrumentation of large civil structures possible. In fact, it is widely anticipated that ad-hoc networks of hundreds of sensors will soon be deployed in practice. As a result, it is important for researchers to translate traditional system identification techniques to a distributed setting for use in wireless sensing networks.

In this paper, three output-only modal identification techniques are adopted and modified for use within a distributed wireless sensing network: the peak picking (PP) method, the random decrement (RD) method, and the frequency domain decomposition (FDD) method. This work sets itself apart from current work in distributed data processing using wireless sensors by maximizing the use of the parallel data processing environment available within large sensing networks. Parallel and distributed computing minimizes the need for interprocess wireless communication which is more power consuming than local processing. This parallel approach, while still addressing problems associated with power consumption and bandwidth, allows a wireless sensing network to employ typical offline modal analysis techniques to autonomously extract spatial modal information from a large network of sensors without the need for a central data repository. In order to validate the performance of these embedded algorithms, the cantilevered balcony of a historic theater in metropolitan Detroit is instrumented with a dense network of wireless sensing prototypes. Over the span of several vibration tests, acceleration response data from the balcony is collected by the wireless network. Using the stored data, each of the distributed modal identification techniques is executed to estimate the modal properties of the system. For validation purposes, results from the embedded algorithms are compared with modal analysis techniques run offline using the time history data of the wireless network.

Distributed Implementation of Output-Only Modal Identification Techniques on a Wireless Sensor Network

In general, it is very difficult to excite a large civil structure in a controlled manner. As a result, several output-only modal estimation methods have been adopted for common use in structural system identification. In this paper, three of these methods are modified for a distributed setting and implemented on a network of wireless sensing prototypes. The first method is the PP method (Ewins 1986; Allemang 1999). This frequency domain method is commonly used in civil engineering because of its simplicity. The second method is the FDD technique (Brincker et al. 2001b), which is similar to peak picking but is much more robust when dealing with closely spaced modes. The third method is the RD method (Cole 1968; Ibrahim 1977). In a multiple degree of freedom system, this technique is dependent upon previous knowledge of the system's modal frequencies (which could be provided by the PP algorithm), but it offers a superior way of determining accurate estimates for modal damping values. In this section, the theory behind each of these methods and their distributed implementation within a wireless sensing network is described in detail.

Peak Picking Method

The PP method is the simplest known technique for estimating the modal properties of a structure from system output data. This method, like many other output-only techniques, assumes that the immeasurable excitation input can be characterized as zero-mean Gaussian white noise. In civil engineering applications, this type of excitation is generally achieved using either impulse or ambient vibration loading conditions. PP analysis is based on the fact that the FRF of a given system will experience extreme values around that system's modal frequencies (Ewins 1986). Assuming a white noise excitation, the FRF of a structure at sensor location k , $H_k(j\omega)$, can be considered equivalent to the Fourier spectrum of the response data collected at that sensor. This spectrum can be formulated by converting measured accelerations to the frequency domain using a fast Fourier transform (FFT).

If a structure is lightly damped with well separated modes, operational deflection shapes (which are correlated to mode shapes) can also be determined with the PP method using the system's FRFs (Allemang 1999). The imaginary component of a FRF at modal frequency ω_i at sensor locations 1 through n , can be assembled to yield the i th mode shape, ϕ_i , as follows: $\phi_i = [\text{imag}[H_1(j\omega_i)] \cdots \text{imag}[H_n(j\omega_i)]]^T$. From the perspective of a wireless sensing network, this method is relatively easy to implement in a decentralized fashion. In this implementation, the user first specifies the maximum number of peaks, p , that should be identified. Then, a consistent set of acceleration time history data is collected at each sensing node and converted to a FRF using an embedded version of the Cooley–Tukey FFT algorithm. Each node picks the p largest peaks from its frequency response function by scanning for frequencies at which the value of the FRF is significantly and consistently higher than the value of the FRF at surrounding frequencies. If less than p peaks are found, zeros will be returned in place of the missing peaks. This algorithm assumes that there are no closely spaced modes and thus can only detect peaks separated by at least ten points on the frequency spectrum. Because some sensing nodes may not be capable of detecting peaks at all modal frequencies due to positioning or poor data, it is necessary to transmit peak information to a central node that can view the individual PP results for the network as a whole. It should be noted that every wireless sensor communicates its identified peaks (p of them) to the central node; hence, the amount of data to be transmitted is fixed. By tabulating the periodicity at which a given frequency has been “picked” by nodes on a network, this central node can infer a subset of p (or fewer) reasonable modal frequencies from the original PP data. Once the central node has determined a global set of peak frequencies, it can then share its findings (namely modal frequencies) with the rest of the network, and the imaginary components of the FRFs at the picked frequencies can be transferred from each sensor to the rest of the network, one sensor at a time. This sharing of data provides all wireless sensor nodes with mode shape information. If necessary, other local data (such as time histories or frequency spectra) can be subsequently communicated by each wireless sensor to a central server in the network. A graphical representation of the implementation of the PP method on a distributed network of wireless sensors can be seen in Fig. 1.

By limiting the amount of necessary communication between individual sensing units, this approach drastically limits the amount of bandwidth needed for wireless data transmission. For example, if in a centralized sensing network 20 wireless sensors are used to send data to a central server for modal estimation, then 4,096 data points are transmitted from each unit resulting in

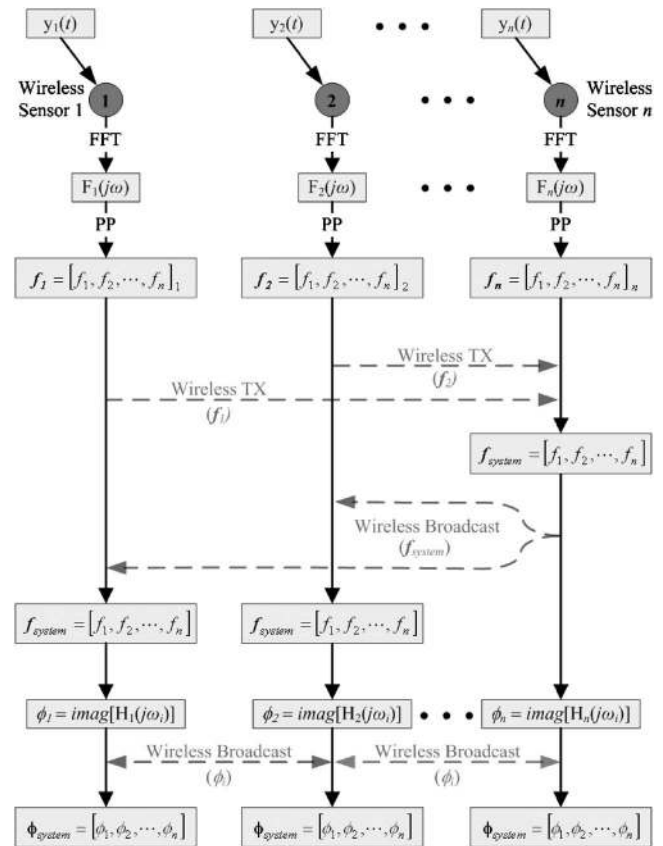


Fig. 1. Implementation of peak picking method on a network of wireless sensors

163,840 total bytes being transmitted (each point is a 2 byte number). If the central server communicates modal information to each node in a peer-to-peer configuration, an additional 7,040 bytes are transmitted (bringing the total number of bytes to 170,880). However, should the central server be able to broadcast to the entire network, then only an additional 352 bytes need to be transmitted (bringing the total number of bytes to 164,192).

In a similar scenario using the parallel in-network approach to PP outlined above, the same results can be obtained by transmitting a total of only 2,128 bytes of data. In this method, if 19 nodes each send four peak frequencies to a central node, then 340 bytes are communicated. Then, by peer-to-peer communication, the central node would send the final modal frequencies back to the original 19 nodes (requiring an additional 340 bytes). Once each node knows what the network has decided the modal frequencies are, each node in the peer-to-peer network can communicate the imaginary components of their frequency response function so that each node can assemble the four mode shapes of the structure; this requires 1,520 bytes to be communicated. If ideal broadcasting is possible, this approach can be further reduced to require only 640 bytes of communication. A summary of this detailed breakdown can be found in Table 1. This method is also advantageous because it is relatively simple to implement on a sensing network and it utilizes engineering algorithms that can be processed quickly. However, there are several drawbacks to distributed PP analysis. Primarily, peak picking is always a subjective practice, and it is therefore difficult to implement perfectly in software. Additionally, peak picking does not properly handle closely spaced modes.

Table 1. Summary of Wireless Data Transmission Needed in Network with 20 Nodes Where 4,096 Data Points Are Used to Calculate Modal Information for Four Modes

Method	Transmission	Payload type	Bytes	Results	Assumption
Centralized server	4,096 shorts \times 20 nodes	Time history data to server from each node	163,840	$\{a\}$	—
	4 floats \times 20 nodes	4 damping ratios from server to each node	320	$\{\xi_i\}$	—
	80 floats \times 20 nodes	4 mode shapes from server to each node	6,400	$\{\phi_i\}$	—
	4 floats \times 20 nodes	4 frequencies from server to each node	320	$\{f_i\}$	—
	Total		170,880		
Decentralized PP	4 floats \times 19 nodes	4 frequency peaks to central node	304	$\{f_i\}$	—
	4 floats \times 19 nodes	4 modal frequencies back each node	304	$\{f_i\}$	—
	4 floats \times 20 \times 19 nodes	Imaginary components with each node (20) sending to every other node (19)	1,520	$\{\phi_i\}$	—
Total		2,128			
Decentralized FDD	8 floats \times 19 nodes	Spectral value at each mode from one node to a neighboring node	608	$Q(\omega)$	Modal frequencies already known
	8 floats \times 18 nodes	2 node mode shape to central node	576	$\{\phi_i\}$	
	80 floats \times 19 nodes	4 stitched mode shapes back to each node	6,080	$\{\phi_i\}$	
	Total		7,264		
Decentralized RD	4 floats \times 19 nodes	4 identified frequencies to central node	304	$\{f_i\}$	Modal frequencies already known
	4 floats \times 19 nodes	4 identified damping ratios to central node	304	$\{\xi_i\}$	
	4 floats \times 19 nodes	4 modal frequencies back each node	304	$\{f_i\}$	
	4 floats \times 19 nodes	4 modal damping ratios back each node	304	$\{\xi_i\}$	
	Total		1,216		

Note: short=2 bytes; and float=4 bytes.

Frequency Domain Decomposition Method

The FDD technique, developed by Brincker et al. (2001b) maintains most of the advantages of other classical frequency domain methods, such as peak picking. However, the FDD technique approximately decomposes the spectral density matrix into a set of single degree of freedom (SDOF) systems using singular value decomposition (SVD), allowing close modes to be identified with high accuracy. In this method, the relationship between measured responses $y(t)$ and unknown inputs $x(t)$ can be expressed as

$$\mathbf{G}_{yy}(j\omega) = \mathbf{H}^*(j\omega)\mathbf{G}_{xx}(j\omega)\mathbf{H}(j\omega)^T \quad (1)$$

where $\mathbf{G}_{yy}(j\omega) = (m \times m)$ power spectral density (PSD) matrix of the responses; $\mathbf{G}_{xx}(j\omega) = (1 \times 1)$ matrix of the input; $\mathbf{H}^*(j\omega)$ = complex conjugate of the $(m \times 1)$ FRF matrix; $\mathbf{H}(j\omega)^T$ = transpose of the $(m \times 1)$ FRF matrix; and m = number of output degrees of freedom.

In the FDD method, the first step is to obtain an estimate of the output PSD matrix, $\hat{\mathbf{G}}_{yy}(j\omega)$ for each discrete frequency $\omega = \omega_i$. This can be done by creating an array of FRFs using FFT information from each degree of freedom in a system

$$\hat{\mathbf{G}}_{yy}(j\omega_i) = \{F_y(j\omega_i)\}\{F_y^*(j\omega_i)\}^T \quad (2)$$

where $\{F_y(j\omega_i)\}$ = array of FFT values for each degree of freedom at a given frequency ω_i and $\{F_y^*(j\omega_i)\}^T$ = complex conjugate transpose (Hermitian matrix) of that array (Allemang 1999).

The second step in the FDD process is to extract singular values and singular vectors from the PSD of the response by taking the SVD of the matrix $\hat{\mathbf{G}}_{yy}(j\omega)$

$$\hat{\mathbf{G}}_{yy}(j\omega_i) = \mathbf{U}_i \mathbf{S}_i \mathbf{U}_i^H \quad (3)$$

where the matrix $\mathbf{U}_i = [u_{i1}, u_{i2}, \dots, u_{im}]$ = unitary matrix holding singular vectors u_{ij} ; \mathbf{S}_i = diagonal matrix holding the scalar singular values s_{ij} ; and \mathbf{U}_i^H = Hermitian matrix of \mathbf{U}_i . Near a peak in the PSD function corresponding to a given mode in the spectrum, this

mode or a possible close mode will be dominating. Thus, the first singular vector, u_{i1} , can be an estimate of the mode shape ϕ_i : $\hat{\phi}_i = u_{i1}$. An extension of the FDD method that allows for the detection of additional modal information (i.e., modal frequencies and damping ratios) is often called enhanced frequency domain decomposition (EFDD), and was originally proposed by Brincker et al. (2001a). However, in this study the FDD method will only be used to determine system mode shapes.

Unfortunately, because of the need to store and manipulate the output power spectral density matrix for each degree of freedom in a system, the implementation of a centralized FDD method requires a significant amount of memory relative to the PP method. On a wireless sensing network where there are heavy constraints on the amount of available storage at each sensing node, an alternate decentralized method is proposed and implemented. The key feature of this approach is that mode shapes are determined by creating a collection of overlapping two-node modes and stitching them together after computation is complete.

First, the wireless sensing network collects a synchronized set of time history acceleration data. This set of data is then transformed to the frequency domain via an embedded FFT algorithm, and the aforementioned embedded PP technique is employed to identify modal frequencies at each node on the network. Peak picking results are then transmitted wirelessly to a central node, where a final set of modal frequencies are decided upon and shared among the nodes in the network. At this point, every unit in the network transmits its complex FFT results corresponding to the picked modal frequencies to the next unit in a predetermined chain (except for the last unit in the chain, which has no successor). Using this shared data, all but one of the sensing nodes (the first in the chain) is able to construct a two degree of freedom output PSD matrix at each modal frequency using the two sets of FFT results. After each wireless sensor performs a SVD on the PSD matrix, two-node mode shapes are extracted from the resulting singular vectors at the frequencies previously determined by

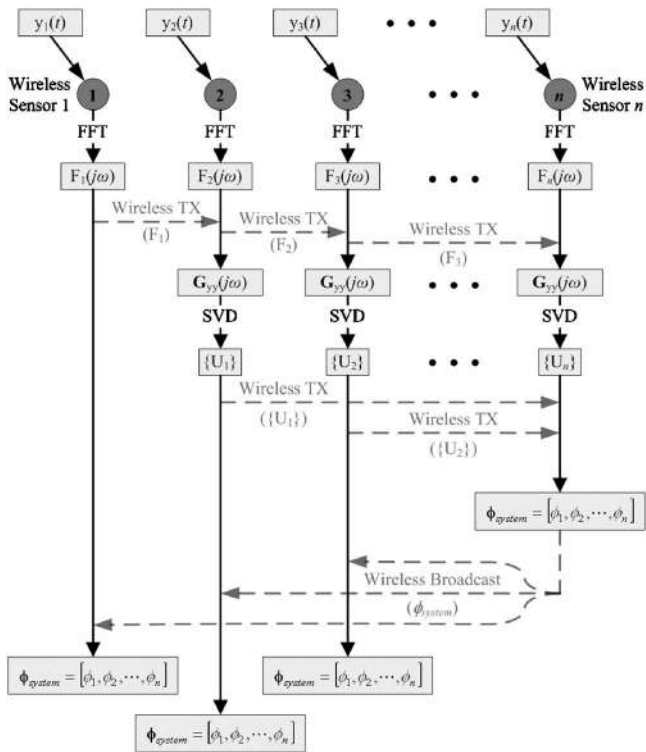


Fig. 2. Implementation of frequency domain decomposition method on a network of wireless sensors, assuming previous knowledge of modal frequencies

PP. Finally, all two-node mode shapes are transmitted back to a central node, where they are recombined to form full system mode shapes; global mode shapes are then shared with the entire network. A graphical representation of this decentralized FDD method embedded within a network of wireless sensors can be seen in Fig. 2. It is also possible to extract damping information from the SVD results for each two-node mode shape by performing an embedded inverse FFT (IFFT) on its SDOF PSD function and calculating its logarithmic decrement. In this study, however, all FDD damping estimates are performed offline. If desired, a user can also request complete recorded time histories, FFT information, and complete SVD results from each unit.

This approach requires slightly more wireless communication than the PP method. Assuming modal frequencies have been previously identified, the decentralized FDD method requires a total of 7,264 bytes to be communicated in a 20 node network, as summarized in Table 1. In the current implementation, data communication is done by peer-to-peer communication links. However, the number of bytes to be communicated could be reduced to 1,504 if the central node is able to broadcast the global modes to all of the network nodes as opposed to one at a time as is currently implemented. As seen in Table 1, these numbers are significantly less than the 170,880 bytes of data required in the centralized setting. As such, while the distributed FDD analysis technique presented above requires significantly more computation than does peak picking, it is effective in limiting the amount of data transmission necessary to ascertain modal frequencies and mode shapes. In addition, the implemented FDD method provides more reliable and robust mode shape estimates compared to PP, especially in the case of closely spaced modes. Additionally, because all FFT and SVD computations are performed simultaneously in a parallel fashion, significant time savings can be

realized from the parallel implementation. As a result, this method can be made scalable to an almost infinite number of nodes.

Random Decrement Method

The RD technique is based upon the concept of the “random decrement signature,” proposed initially by Cole (1968), and explored in greater detail by Ibrahim (1977) and Asmussen (1997). This concept essentially states that the response of a single degree of freedom structure due to a random input is composed of a deterministic impulse part and a random part with an assumed zero mean. Thus, by averaging enough samples of the same random response, the random part will average out, leaving only the deterministic part of the signal. In order to avoid averaging out the deterministic part of the signal, random decrement analysis consists of averaging N windows of length τ . Each of these windows must always start with one of the following:

1. A constant level, which yields the free decay step response;
2. Positive slope and zero level, which yields the free decay positive impulse response; and
3. Negative slope and zero level, which yields the free decay negative impulse response.

Thus, if $y(t)$ =random response, the free decay impulse response, $x(t)$, can be written as

$$x(\tau) = \frac{1}{N} \sum_{n=1}^N y(t_n + \tau) \quad (4)$$

with the condition $t=t_n$, when $y(t)=y_s$ =constant level; or $y(t)=0$ and $dy/dt > 0$; or $y(t)=0$ and $dy/dt < 0$.

The response resulting from applying the random decrement signature technique is equivalent to the free decay response of the structure. From this free response function, modal frequencies can be extracted by examining zero crossings; and modal damping can also be estimated using the logarithmic decrement of the decay function. In a multiple degree of freedom structure, the random decrement response for each mode can be calculated by taking the time history response of the structure to the frequency domain, and filtering out all frequencies that do not correspond to a given mode.

In this study, a distributed RD algorithm is designed and embedded within the computational core of a network of wireless sensors so that the network can autonomously estimate modal frequencies and damping ratios. For this algorithm, a set of consistent time history acceleration data is first collected at each sensing node. Each node in the network then transfers its data to the frequency domain using an embedded FFT. Employing a frequency window provided by the user (or calculated from prior peak picking information), frequencies irrelevant to a given mode are filtered out, and the signal is taken back to the time domain using an embedded IFFT. This window is specific to one modal frequency, and thus the RD process must be repeated for each mode. At this point, a summation trigger y_s (which is also designated by the user) is used within each sensing node to create a number of samples for random decrement averaging. These samples are converted into a SDOF free decay impulse response function by applying the concepts in Eq. (4). Zero crossing and logarithmic decrement techniques are employed to automatically extract modal frequency and damping information from the impulse response. These parameters, calculated independently in each node in the network, can then be sent wirelessly to a central node where a systemwide modal frequency and damping ratio can be determined using statistical measures and broadcast to the net-

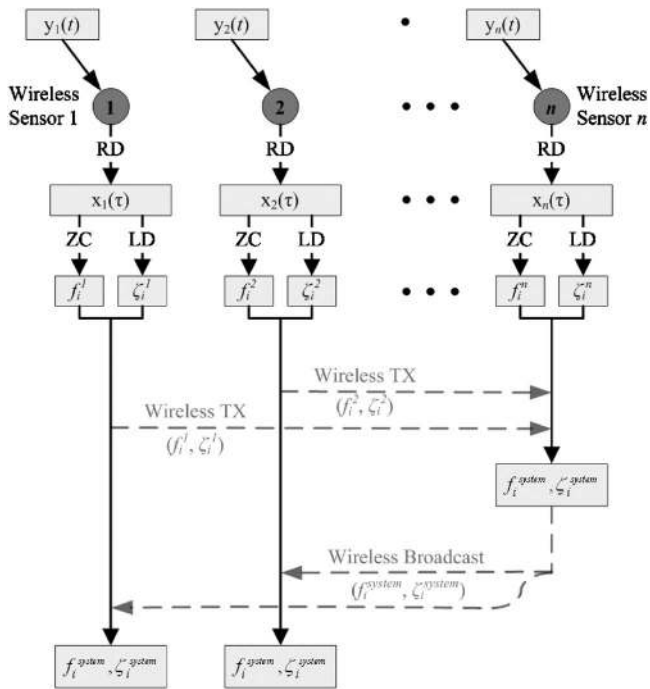


Fig. 3. Implementation of random decrement method on a network of wireless sensors, assuming previous knowledge of approximate modal frequencies

work. A graphical representation of the distributed RD algorithm can be found in Fig. 3. Note that it is also possible to extract mode shapes using embedded RD analysis by choosing a common lead node with which to trigger the RD averaging (Ibrahim 1977). However, in this study, the RD method is only used to calculate modal frequencies and damping ratios.

Much like the embedded PP method, this decentralized RD technique greatly limits the amount of data needed to be transmitted wirelessly. In a network with 20 nodes, where 4,096 points of data from each sensor are being used to calculate modal information for four distinct modes, the decentralized RD method presented above requires only 1,216 bytes of data to be transmitted wirelessly. However, it does rely on previous knowledge of approximate modal frequencies. Thus, as seen in Table 1, this method, when used in conjunction with the decentralized PP algorithm, can provide accurate estimates of modal frequencies and damping ratios by transmitting a total of only 3,344 bytes of data. In a wireless network allowing for ideal broadcasting, this number can be reduced to a mere 1,040 bytes. This is a significant improvement over the requirements of the centralized setting. The decentralized RD method is also rather simple to implement on a wireless sensing network and utilizes engineering algorithms that can be processed quickly. This method provides accurate estimates of modal damping ratios by taking advantage of the great degree of redundancy available within a sensing network. However, in a multiple degree of freedom system, prior knowledge of the frequency characteristics of the system (possibly obtained from an embedded PP analysis) is required in order to properly window the Fourier spectrum. This method is also not suited to determining modal properties involving closely spaced modes.

Experimental Testbed

Theater Balcony

A historic theater, located in metropolitan Detroit, is selected as an appropriate structure to validate the embedded algorithms proposed for use within a wireless sensing network. This theater is one of the largest in the United States, and is part of a large complex which includes several theater service areas and an attached office building. The auditorium itself has two balconies: a main balcony located at the fifth floor level of the building, and a loge balcony located at the third floor level. The main balcony, shown in Fig. 4(a), is chosen for instrumentation purposes. This balcony is approximately 50 m (150 ft) wide, and is structurally supported only at the rear and sides of the auditorium. As a result of its long unsupported span, the theater's balcony is known to suffer from humanly perceptible vibrations (Setareh 1990).

Instrumentation and Excitation Strategy

On February 2, 2007, the front section of the main balcony of the theater [specifically the first five rows within a 3 m (15 ft) band of the balcony edge] was instrumented using a network of wireless sensors. These sensors, proposed by Wang et al. (2005) and shown in Fig. 5, are capable of 16-bit data collection on four simultaneous sensor channels and can communicate data up to 300 m on the 900 MHz radio band. A low-power 8-bit microcontroller is included in the wireless sensor design for local data processing, and a rich library of data interrogation algorithms have been included in the operating system (Lynch 2007). Powered by five AA batteries, these units can operate for 30 h. Various instrumentation studies of the unit on various long-span bridges have validated the accuracy of the system (Lu et al. 2006; Hou and Lynch 2006; Wang et al. 2006, Lynch et al. 2006), including tight time synchronization [i.e., a synchronization error of less than 5 ms between nodes (Lynch et al. 2006)].

In this study, 21 wireless sensing units were installed in a 7×3 grid, with seven units distributed evenly across the span of the balcony in each of rows 1, 3, and 5. The location of these sensing units is shown in Fig. 4(c). Attached to each wireless sensing unit was either a PCB Piezotronics 3801D1FB3G micro-electro mechanical system (MEMS) capacitive accelerometer or a Crossbow CXL02LF1Z MEMS capacitive accelerometer; each was oriented to monitor the vertical acceleration of the balcony. The sensitivity of the PCB accelerometer is 0.7 V/g and its dynamic range is 3g, peak-to-peak. The sensitivity of the Crossbow accelerometer is 1.0 V/g and its dynamic range is 2g, peak-to-peak. To improve the performance of the wireless monitoring system, a signal conditioning circuit proposed by Lynch et al. (2006) was included with each sensor to both amplify and band-pass (0.02–25 Hz) acceleration response data before inputting to the wireless sensor's ADC. This circuit essentially amplifies the accelerometer output so that the noise floor of the accelerometer controls the data quality as opposed to the quantization error of the ADC; this is especially useful for ambient structural accelerations. To verify the integrity of the wireless monitoring system, two additional tethered acceleration channels were monitored using a cable-based Freedom Data Acquisition System PC from Olson Instruments, Inc.; this system comes equipped with its own data acquisition software. Internally, data acquisition is accomplished using a National Instruments 1.25 MS/s, 16-channel 12-bit PCI data acquisition card. Tethered Dytran accelerometers (Models 3165A and 3116A) were employed with the Freedom

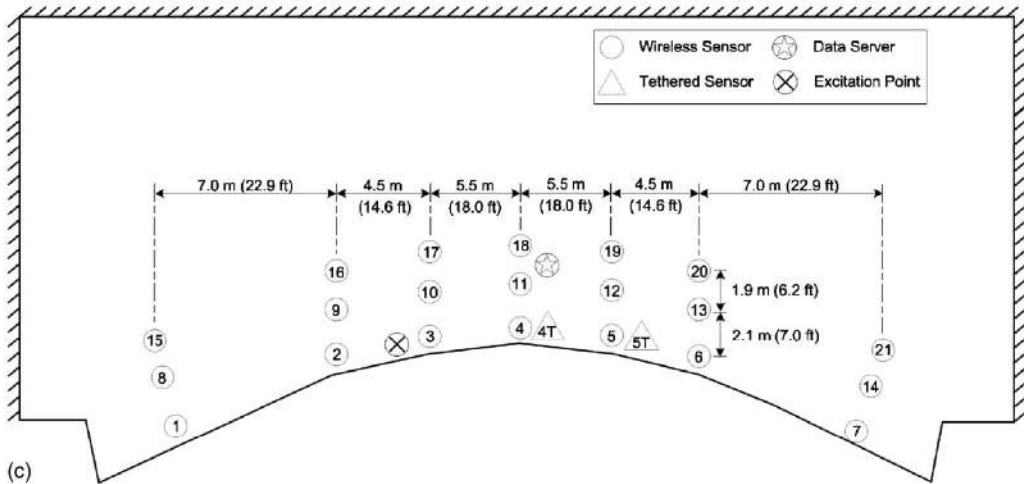
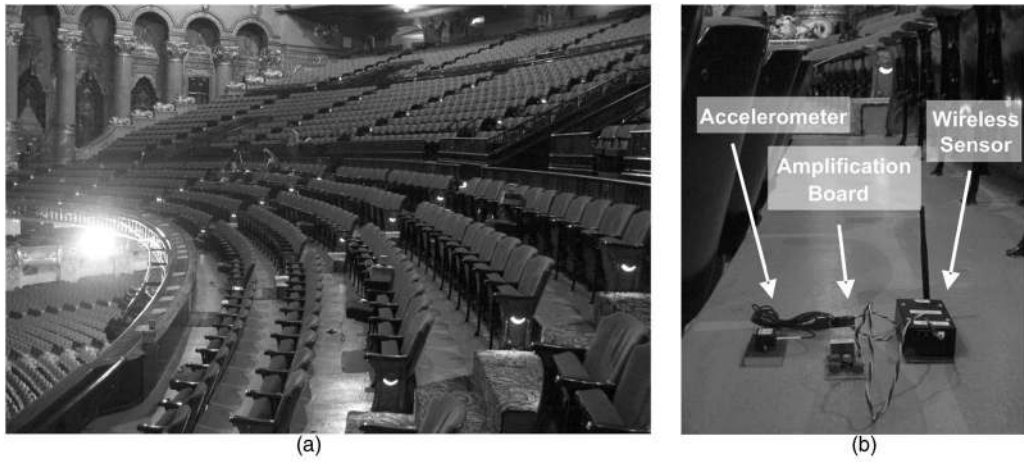


Fig. 4. Wirelessly instrumented theater balcony: (a) main balcony; (b) typical wireless sensor layout; and (c) location of wireless and tethered accelerometers (plan view not drawn to scale)

system. These accelerometers have sensitivities of 1.0 V/g with a dynamic range of $\pm 5g$. As seen in Fig. 4(c), the locations of the tethered sensors are collocated with wireless sensors 4 and 5; as a result, tethered sensors are denoted as 4 T and 5 T, respectively.

Because all three output-only identification methods previously presented assume a broadband white input, an appropriate method of excitation had to be adopted for testing. For the purposes of this study, impulsive excitation was delivered using a simple heeldrop test. This type of loading is performed by quickly raising and dropping both heels simultaneously. This test is typically thought to mimic an impulse load. The location of this heeldrop loading was between sensor 2 and sensor 3 at the front of the balcony, as seen in Fig. 4(d).

Experimental Results

On the day of testing, a set of nine nearly identical tests (denoted as runs Nos. 1–9) were run using impulse loadings generated by a single person weighing 82 kg (180 lb) and performing a heeldrop. The objectives of these tests were to validate the accuracy of the wireless data acquisition system and to compare the ability of the proposed distributed modal identification methods to accurately determine the balcony’s modal parameters (modal frequencies, damping ratios, and mode shapes) using the embedded processing

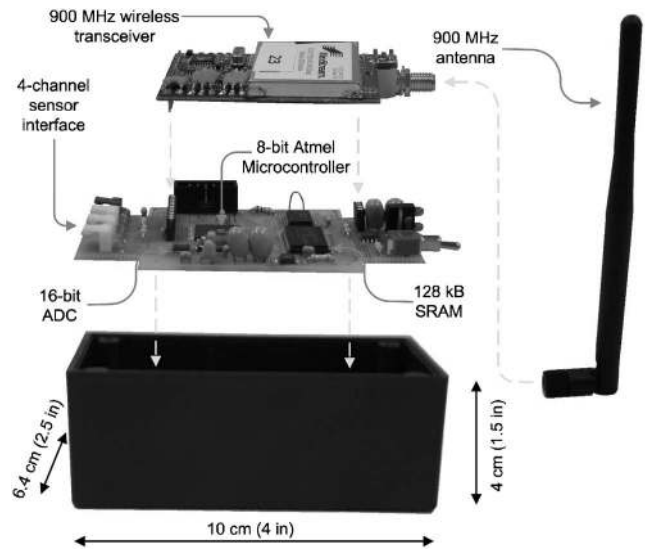


Fig. 5. Wireless sensing prototype with individual components highlighted

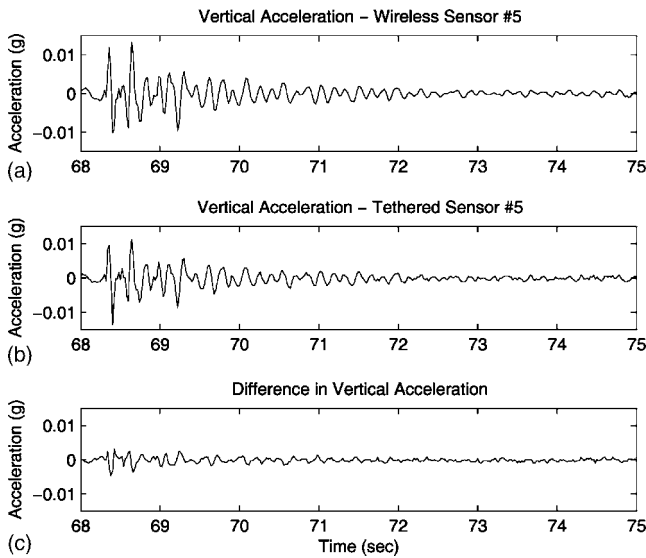


Fig. 6. Balcony response recorded by (a) wireless; (b) tethered monitoring systems at sensor location 5; and (c) difference between two measured histories

capabilities residing on the spatially distributed network of wireless sensor nodes.

Wireless System Performance

The first testing objective was to validate the accuracy of the proposed wireless sensing network against a traditional, tethered monitoring system. During all 15 tests, two channels of tethered acceleration data were collected in parallel with the wireless network. Both monitoring systems employed a sample rate of 50 Hz. If the response of the tethered system is compared alongside that of the wireless system, it can be seen that the recorded time history data is nearly identical, as seen in Fig. 6. In this figure, the response from both monitoring systems is plotted between 68 and

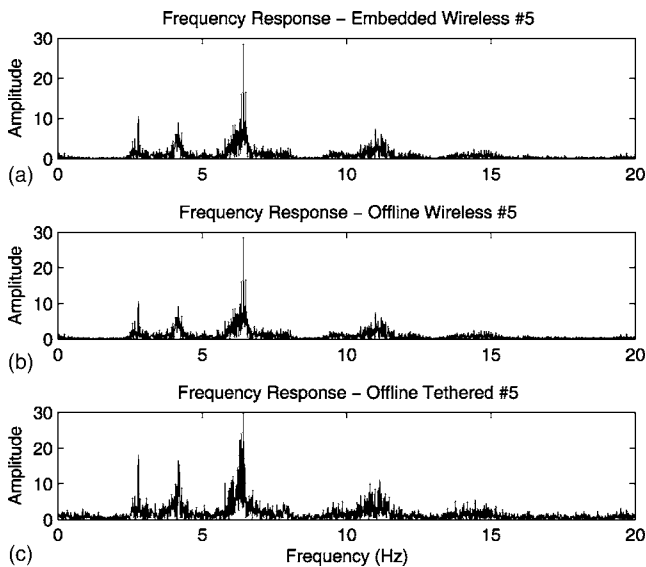


Fig. 7. Fourier spectra for balcony response at sensor location 5: (a) embedded FFT executed by wireless sensor; (b) calculated offline using wireless data; and (c) calculated offline using tethered data

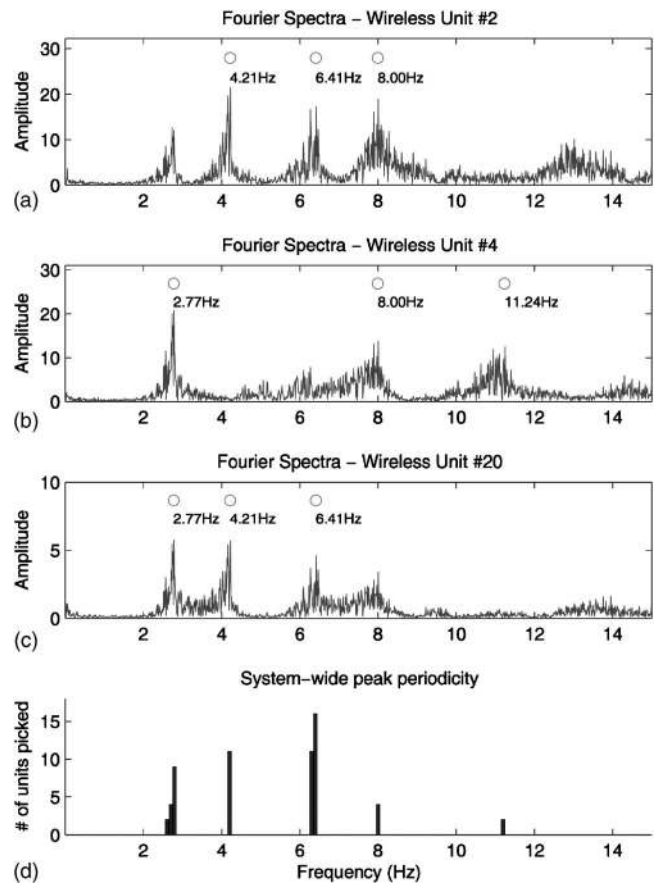


Fig. 8. Embedded PP modal frequency results from: (a) sensor location 2; (b) sensor location 4; (c) sensor location 20; and (d) system-wide distribution of picked peaks tabulated at central wireless sensor node

75 s. Very little discrepancy is observed if the two acceleration time histories are subtracted from one another. Similar results were obtained in other locations and in all testing scenarios.

Embedded Peak Picking Results

The second testing objective was to validate each of the distributed data processing algorithms (PP, FDD, RD) proposed in this study. In order to validate the ability of the PP method to extract modal frequencies from an output-only system, it is necessary to first prove the effectiveness of each of the numerical tools used within this identification technique. The first of these tools is the embedded FFT. In all of the testing runs in which PP analysis was requested, each node of the wireless sensor network was required to calculate a 4,096-point complex-valued Fourier spectrum from the time history data collected. A Fourier spectrum from one sensing location is shown in Fig. 7. For comparison, Fourier spectra calculated offline in Matlab using time history data from the tethered and wireless monitoring systems are also shown. It can be seen that the frequency characteristics extracted from the embedded algorithm are very similar to the results obtained using an offline analysis of either tethered or wireless time history data.

The second numerical tool in question is the embedded PP algorithm itself. This algorithm is required in both the PP and the FDD output-only identification methods presented in this paper. In all of the test cases in which one of these two methods was used, each wireless sensor in the network was asked to extract the

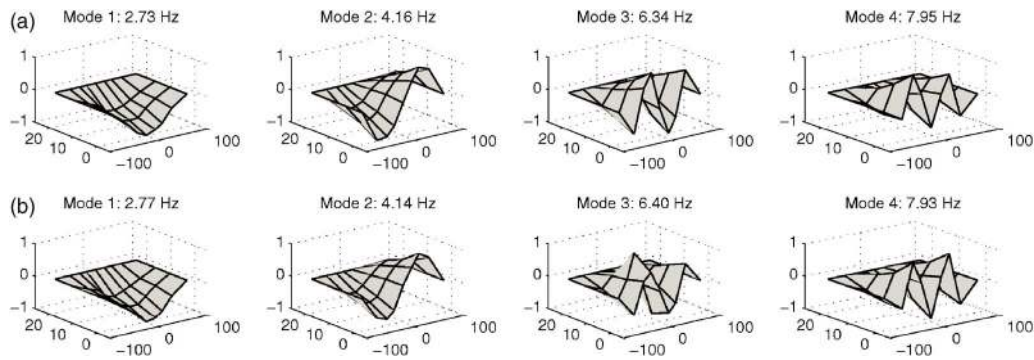


Fig. 9. (a) Offline centralized FDD mode shape results; (b) embedded PP mode shape results based on in-network processing

three highest peaks from the Fourier spectrum created using the embedded FFT algorithm. Because peak picking is a somewhat subjective science, no one sensing unit can be solely relied upon to correctly identify three distinct modal frequencies. As such, PP results from each sensing node must be transmitted to a designated node or central server where an intelligent decision can be made about final modal frequencies. PP results from three different units can be seen in Fig. 8, which also shows the ability of a central server to determine system-wide modal frequencies from a complete set of PP data (compiled from all 21 nodes). It can be seen that by looking at the peak picking results as a whole, a reasonable global estimate of peak frequencies can be extracted from system-wide data. The central node was able to identify system-wide modal frequencies and extract mode shapes for the first (2.77 Hz), second (4.14 Hz), fourth (6.40 Hz), and fifth (7.93 Hz) modes. Note that the third mode (5.11 Hz) is absent, as the chosen excitation point did not provide adequate spectral content at this modal frequency for proper peak picking mode detection. Fig. 9 compares a set of mode shapes calculated using the embedded PP method with a set of mode shapes calculated offline using the centralized FDD technique. Numerical comparisons between modal frequencies and mode shapes calculated using the two methods are presented in Table 2. In this table, mode shapes determined with peak picking are compared with the offline FDD modes using the modal assurance criteria (MAC), as defined by Allemang and Brown (1982). Strong agreement is observed in the modal frequencies and mode shapes between those derived by the wireless sensor network and those found off-line using a centralized server running Matlab. Modal frequencies are within 1% of one another while MAC values of 0.9 or greater are observed in most modes.

Embedded Frequency Domain Decomposition Results

The second embedded modal identification method presented in this paper is the FDD technique. This method was chosen for this

study because of its advantages over peak picking when estimating mode shapes from output response data. When implemented within a wireless sensing network, this method creates a large array of overlapping two-node mode shapes, which can be easily assembled at a later time by a central processor (either a designated node or a server). This distributed technique provides a great degree of scalability by parallelizing a typically centralized algorithm to be executed by a community of wireless sensor nodes. As such, three distinct network topologies were designed and tested for the sharing of Fourier spectra and the creation of two-node mode shapes. As can be seen in Fig. 10, data sharing in each of the three network topologies begins with the same root node (wireless sensor 1), but creates a very different set of two-node pairs. Each topology is meant to test different nodal overlaps so as to observe the sensitivity of the distributed FDD method to topology and to validate the scalability of this method. Because it has been shown that a very small synchronization error (with a maximum of 5 ms) may occur between distantly spaced nodes, the assumption is that topologies with closely spaced two-node mode shapes should behave better than topologies with distantly spaced nodal connections. Additionally, it is assumed that increased symmetry within a topology will lead to a decrease in mode shape accuracy, depending on the nodal locations of the detected modes. Fig. 11 displays the extracted mode shapes using these three distinct network topologies in addition to the mode shapes found using an offline centralized FDD method. Because of the loading location, the third mode (5.11 Hz) was not captured in each of these cases. Table 3 provides a numerical comparison between mode shapes calculated using the embedded FDD method and those calculated offline. Again, these mode shapes are compared using the MAC, and MAC values of 0.9 or greater are typically obtained for the network determined modes.

It can be seen from Fig. 11 that the first topology provides excellent mode shape estimates for all four detected modes. However, the fourth mode in the second topology and the third mode

Table 2. Summary of Modal Identification Results from Embedded Peak Picking Method

Method	Run	Natural frequency (Hz)				MAC			
		Mode 1	Mode 2	Mode 4	Mode 5	Mode 1	Mode 2	Mode 4	Mode 5
Centralized FDD (off-line)	1	2.734	4.163	6.335	7.946	1.000	1.000	1.000	1.000
	2	2.727	4.210	6.349	7.996	—	0.949	0.937	0.779
Peak Picking (embedded)	3	2.734	4.135	6.342	8.020	0.825	0.678	0.427	0.817
	4	2.772	4.144	6.396	7.929	0.990	0.973	0.869	0.944

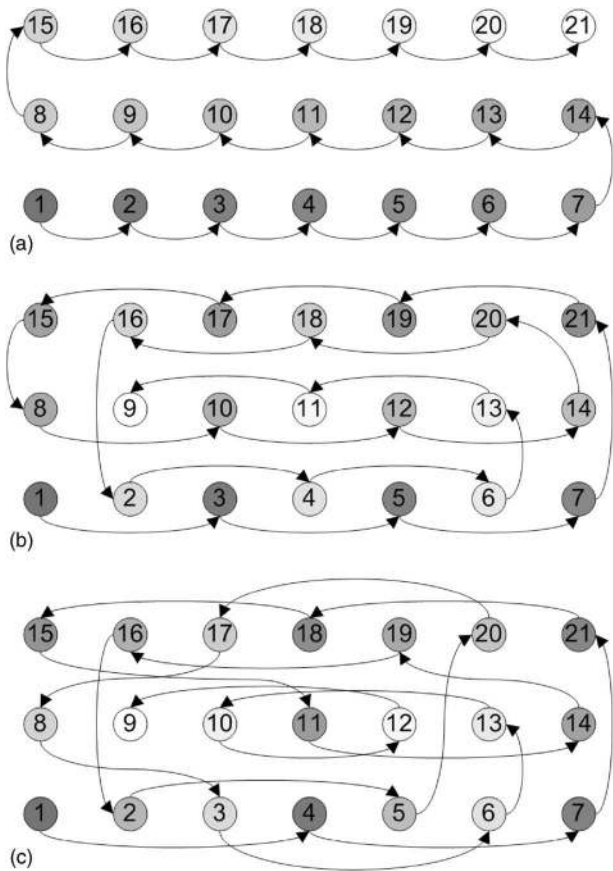


Fig. 10. Network topologies for two-node FDD data sharing (arrows and shading indicate transmission of Fourier spectra for two-point mode determination): (a) topology 1; (b) topology 2; and (c) topology 3

in the third topology appear to be somewhat inconsistent with the mode shapes calculated using a centralized FDD ($MAC < 0.9$). This is most likely due to the nodal locations of the third and fourth modes, as well as symmetry between two-node pairs in the second and third topologies. Because of the impact that topology can have on the accuracy of mode shapes extracted with this distributed FDD technique, more work is required to fully understand the effects of topology choice on this method.

Embedded Random Decrement Results

The third distributed system identification technique implemented on the wireless sensor network in the study is the RD method. For each test in which the RD method was used, each sensor on the network collected a consistent set of time history data. Using the RD algorithm, this time history response was transformed at each node into a SDOF free decay response function using a user-defined trigger amplitude (which is defined as a certain percent of the standard deviation of the time history response) and frequency window (e.g., 2.0 to 3.5 Hz for mode 1, etc.) meant to target a specific mode. Fig. 12 shows an output response time history alongside a random decrement free decay response for each of the first two modes, calculated by wireless sensors 4 and 6, respectively. It can be seen that by employing zero crossing and logarithmic decrement techniques on the resulting free decay response functions, estimates of modal frequencies and damping ratios can be determined at each sensing location. The type of quality result seen in Fig. 12 was repeated in each testing instance and at almost all sensing locations. Once collected at the individual sensor, modal frequency and damping data can be shared with a centralized node or server and a global set of modal frequencies and damping ratios can be determined by throwing out outliers and averaging the remaining results. After averaging, the distributed

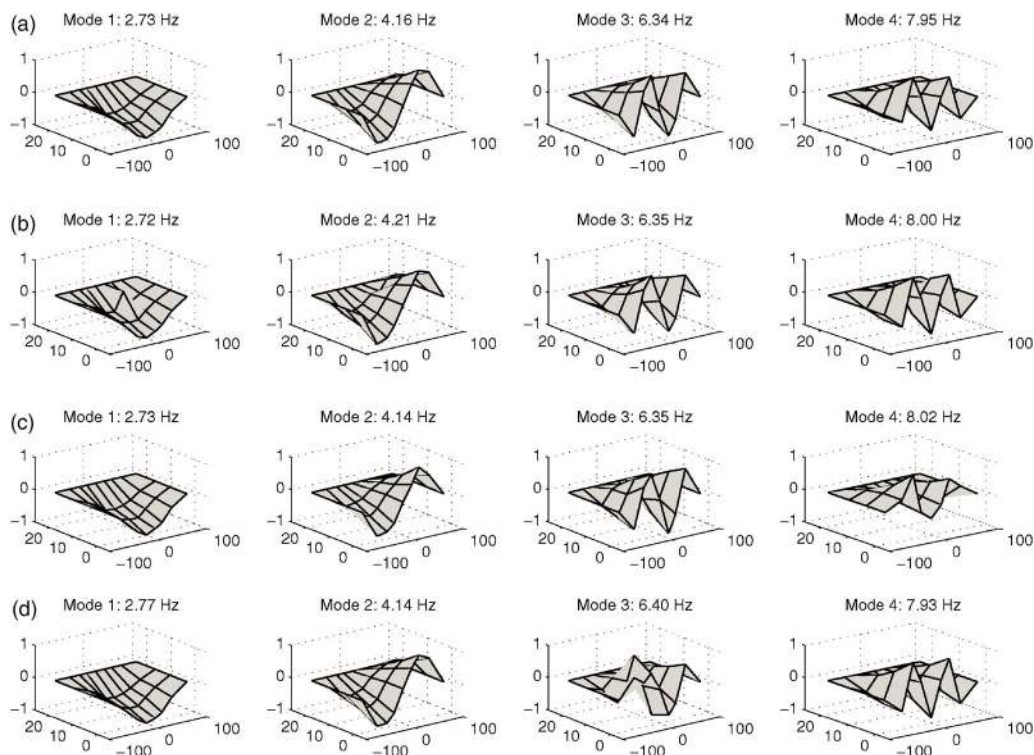


Fig. 11. (a) Offline centralized FDD mode shape results and embedded FDD mode shape results for (b) topology 1; (c) topology 2; and (d) topology 3.

Table 3. Summary of Modal Identification Results from Embedded Frequency Domain Decomposition Method

Method	Run	MAC			
		Mode 1	Mode 2	Mode 4	Mode 5
Centralized FDD (off-line)	1	1.000	1.000	1.000	1.000
	5	0.957	0.985	0.961	0.840
Decentralized FDD (embedded)	6	0.988	0.943	0.821	0.373
	7	0.994	0.984	0.630	0.960

RD method produced system-wide modal frequencies of 2.74 and 4.16 Hz and damping ratios of 1.79 and 1.86% for the first two modes. These results are compared with offline results obtained using a centralized EFDD method and are displayed in Table 4.

Summary and Conclusions

Structural monitoring systems have become increasingly popular for monitoring the response characteristics of large civil structures subjected to ambient and forced vibrations. By leveraging wireless communication technology, wireless monitoring systems can be installed at a fraction of the cost and in much higher sensor densities than traditional tethered sensing systems. In addition to these cost savings, however, wireless sensors have an enormous advantage over their tethered counterparts because of their local analog-to-digital conversion and data processing capabilities. By taking advantage of the embedded computing resources distributed across a large network of wireless sensors, decentralized wireless health monitoring systems can perform as well as centralized tethered systems.

In this study, three existing output-only system identification techniques were modified for a parallel processing environment and embedded within a network of wireless sensing prototypes. In February 2007, a 21-node wireless monitoring system was deployed on the balcony of a historic theater in metropolitan Detroit. With accelerometers attached to the wireless sensors, the acceleration response of the balcony was measured during a set of vibration tests. To excite the balcony with white noise frequency characteristics, heeldrop impact loading methods were employed.

Using the embedded output-only modal parameter estimation methods proposed in this study, the wireless monitoring system was shown to be capable of collecting and processing measured

data at the individual sensor. The wireless network was able to autonomously determine modal frequencies using a distributed PP algorithm, mode shapes using a distributed FDD method, and modal damping ratios using a distributed RD technique. It can be seen that the embedded techniques yield modal parameters comparable to those obtained using traditional offline analyses.

This study represents the successful implementation of distributed modal parameter estimation techniques within the computational core of a network of wireless sensing prototypes. However, further research is still needed to extend existing distributed computing concepts to other system identification and damage detection methods. Both new and existing distributed techniques need to be further validated in increasingly large-scale networks, and must be deployed in long-term structural health monitoring situations. To successfully accomplish these tasks, work must be done to improve the power efficiency of current wireless devices and to enhance the efficiency of local data processing techniques when applied in increasingly dense sensing networks.

Acknowledgments

This research was partially funded by the National Science Foundation (Grant No. CMS-0528867) and the Office of Naval Research Young Investigator Program. Additional support has been provided to Mr. Andrew Zimmerman by the National Defense Science and Engineering Graduate Fellowship (NDSEG) Program. The writers would like to express their gratitude to Mr. David Saftner for his invaluable dedication to this project. Additional support in the form of advice and logistical planning was offered by Professor M. Setareh (Virginia Tech); his assistance was invaluable to the success of this work.

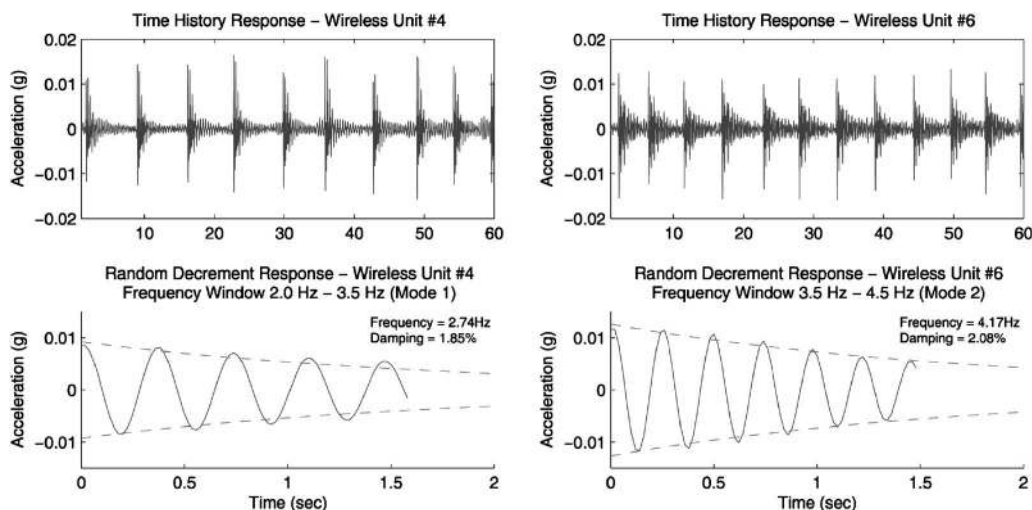


Fig. 12. Embedded RD modal frequency and damping results

Table 4. Summary of Modal Identification Results from Embedded Random Decrement Method

Method	Run	Natural frequency (Hz)		Damping ratio (%)	
		Mode 1	Mode 2	Mode 1	Mode 2
Centralized FDD (off-line)	1	2.734	4.163	2.321	1.610
Random decrement (embedded)	8	2.740	—	1.792	—
	9	—	4.159	—	1.864

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