Automated identification of modal properties in a steel bridge instrumented with a dense wireless sensor network

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ABSTRACT: Wireless sensing technology has made it possible to instrument large civil structures, such as bridges, with dense networks of wireless sensors. Because many wireless sensing platforms integrate data processing capabilities with high-precision analog-to-digital converters, it is possible to autonomously process sensor data without the need for a central data server. By employing parallel processing techniques on typically serial modal analysis methods, a network of sensors can be used to autonomously determine modal properties (modal frequencies, damping ratios, and mode shapes). In this study, distributed versions of three output-only modal identification techniques (peak picking, random decrement, and frequency domain decomposition) are modified for implementation within a wireless sensing platform designed for bridge monitoring. A network of wireless sensors are deployed on 30m long pedestrian bridge; this wireless monitoring system is used to autonomously determine the bridge’s modal properties.

1 INTRODUCTION

One of the key responsibilities of today’s structural engineering profession is to help maintain the long-term health and stability of society’s civil structures (bridges, buildings, pipelines, tunnels, among others). In the wake of tragedies like the I-35W bridge collapse in Minneapolis (August 1, 2007), the catastrophic consequences of allowing our civil infrastructure to degrade are self-evident. As such, structural health monitoring (SHM) systems have become increasingly important to the structural engineering community. These systems, which typically consist of a dense network of sensors, a centralized data repository, and a set of automated data processing tools, can easily reduce routine maintenance and inspection costs by collecting and analyzing structural data with minimal human involvement.

While large sensing networks have been installed successfully in structures around the world (Ko and Ni 2005), the commercial viability and widespread adoption of SHM systems has been stymied by the high cost of installing and maintaining the extensive lengths of wiring needed in a large civil structure to connect individual sensors to a central repository. As a result of these high costs, wireless sensing technologies have emerged as a cost-effective replacement for traditionally tethered sensing systems. In the last decade, numerous wireless sensing platforms have been developed for both academic and commercial use (Lynch and Loh 2006). A fusion of sensing and communication functionality takes place within a wireless sensor, with analog-to-digital converters (ADCs) included for data acquisition, low-power microprocessors for embedded data analysis, and wireless radios for data transmission. Because each individual sensor has the ability to autonomously collect, analyze, and share data, wireless sensing devices have come to be labeled as “smart” sensors (Spencer et al. 2004).

An SHM system built around these “smart” devices has several distinct advantages over a traditional monitoring system. Primarily, because a wireless sensing channel can be installed for a fraction of the cost of a cabled sensor, dense networks of wireless sensors can be affordably deployed in large structures, making an increased amount of structural data available for analysis.
Additionally, because each wireless device has the ability to locally process data, the need to transmit long records of time history data from each sensor to a central processing station is eliminated. This processed data is typically a fraction of the size of the original time history record; hence, power consumption and network bandwidth problems associated with wireless networks can be minimized.

Many researchers have performed local data processing tasks such as autoregressive model fitting, wavelet transforms, and fast Fourier transforms within a wireless sensing environment (Lynch 2007). These algorithms are typically performed independently in each individual sensor, meaning that a central data repository is needed to compile the results and extract system-wide spatial information. However, by utilizing each sensor in the network as a processing node in a massively parallel system, spatial modal information can be extracted from a large network of sensors without the need for a central server. In the SHM context, this paradigm is attractive because it allows a network of sensors to autonomously determine structural damage.

In this study, three output-only modal identification techniques which have been modified for parallelization by Zimmerman et al. (2008) are implemented for the first time within the Narada wireless sensing platform. These methods are the simple peak picking (PP) method, the random decrement (RD) method, and the frequency domain decomposition (FDD) method. A network of 16 Narada wireless sensors is then deployed on the Bandemer Park pedestrian bridge in Ann Arbor, MI. Over the span of several vibration tests, each of the distributed modal identification algorithms are utilized to determine the global structural modal frequencies, mode shapes, and damping ratios of the bridge. In civil engineering, modal properties (mode shapes, modal frequencies, and modal damping ratios) have been widely used to assess structural performance, calibrate analytical design models, and (in cases of severe damage) detect and locate damage in the wake of natural disasters such as earthquakes. In this case, however, these modal analysis methods are used simply as an illustration of the possible autonomous damage detection capabilities of an intelligent wireless sensing network. For validation, the results obtained from the automated identification techniques are compared with similar modal analysis methods run offline using time history data recorded by the network of wireless sensors.

2 NARADA WIRELESS SENSORS

In this study, the Narada wireless sensing unit developed at the University of Michigan (Swartz et al. 2005) is adopted for the embedment of three modal analysis methods (PP, RD, and FDD). This wireless device, shown in Figure 1, is powered by an Atmel Atmega128 microprocessor with 128kB of external SRAM for computation and data storage. This extended memory space allows the unit to store up to 64,000 data points at any one time. Its wireless communication interface consists of the Chipcon CC2420 IEEE 802.15.4 compliant wireless radio, which makes it an extremely versatile unit for developing large, scalable wireless sensing networks. The Narada wireless sensor utilizes a four channel, 16-bit Texas Instruments ADS8341 ADC for data acquisition, and also has actuation capabilities through the use of a two channel, 12-bit Texas Instruments DAC7612 digital-to-analog converter (DAC). This prototype is powered by a constant

Figure 1. Narada wireless sensing unit.
DC supply voltage whose output is between 7 and 9 volts (the equivalent of five or six AA batteries, respectively), and has an operational life expectancy of approximately 48 hours given constant communication and data analysis demands.

3 DISTRIBUTED MODAL IDENTIFICATION IN A WIRELESS SENSING NETWORK

Modal properties are desirable quantities used in monitoring the performance and health of a civil structure. Unfortunately, because it is often very difficult to excite a large civil structure in a controlled manner, many modal analysis techniques that require a complete knowledge of the input-output relationship cannot be applied in many civil systems. As a result, several output-only methods have been developed and adopted for use by the SHM community. Recently, three of these methods have been adapted for parallel execution in a distributed network of wireless sensing prototypes (Zimmerman et al. 2008). These methods are: the peak picking (PP) method (Ewins 1986), the frequency domain decomposition (FDD) method (Brincker et al. 2001), and the random decrement (RD) method (Cole 1968; Ibrahim 1977). In this study, these parallelized algorithms are further modified for embedding within the flexible communication interface of the Narada wireless sensing platform. Because of the ease with which a network of Narada units can be scaled to very high sensor densities, the modifications made in this study represent the next step towards creating scalable, autonomous data analysis strategies for the health monitoring of large civil structures using wireless sensor networks.

3.1 Peak picking

The peak picking (PP) method is a simple technique for estimating a structure’s modal frequencies and mode shapes using only system output data. This method stems from the fact that the frequency response function (FRF) of a given system will peak at and around that system’s modal frequencies (Ewins 1986). Assuming that a structure is excited with a white noise, broadband input, the Fourier spectrum of the response data collected at sensor location \( k \) can be considered equal to the FRF of the structure at that sensor location. If a structure is lightly damped and has well separated modes, then the imaginary component of an FRF at modal frequency \( \omega_i \), for all sensor locations 1 through \( n \), can be assembled to yield the \( i \)th mode shape, \( \phi_i \), which corresponds to the frequency \( \omega_i \).

This method is easily decentralized for implementation in a wireless sensor network (Zimmerman et al. 2008). First, a consistent set of acceleration time history data is collected at each wireless sensor. This data is converted to an FRF using an embedded version of the fast Fourier transform (FFT). Then, each node picks the largest peaks from its FRF by scanning the frequency response for frequencies at which the FRF is significantly and consistently higher than at neighboring frequencies. Because certain sensing nodes will not be capable of detecting all system-wide peaks due to sensor positioning, each wireless sensor is required to transmit its individually picked frequencies back to a pre-assigned central node. This node can then look at all of the PP results as collected by the entire network and tabulate the periodicity at which certain given frequencies are picked. In this way, the central node can infer a subset of reasonable system-wide modal frequencies and share this information with the rest of the wireless network. At this point, each sensor in the network can broadcast the imaginary components of their individual FRFs at the system-wide modal frequencies to the rest of the network. Because these values can be used to form system-wide mode shapes, this parallelized sharing of data allows each sensing node access to complete modal frequency and mode shape information. While this method is easy to implement and requires only a minimal amount of communication, it cannot properly identify closely spaced modes, and does not provide reliable estimates of modal damping ratios. As such, two additional methods are included herein to make the automated detection of modal properties using a wireless sensor network significantly more robust.

3.2 Frequency domain decomposition

The frequency domain decomposition (FDD) technique, which was developed by Brincker et al. (2001), improves upon the PP method by allowing closely spaced modes to be identified with
great accuracy by approximately decomposing the spectral density matrix into a set of single
degree of freedom (SDOF) systems. In order to accomplish this, an estimate of the output power
spectral density (PSD) matrix, $\hat{G}_{yy}(j\omega)$ is first obtained for each discrete frequency $\omega = \omega_i$ by
creating an array of FRFs using FFT information from each degree of freedom in a system.
Then, by taking the singular value decomposition (SVD) of the matrix $\hat{G}_{yy}(j\omega)$, singular values
and singular vectors can be extracted from the PSD. Near a peak in the PSD function corre-
sponding to a given mode in the spectrum, this mode or a possible close mode will be dominat-
ing, meaning that the first singular vector, $u_{i1}$, can be interpreted as an accurate estimate of the
mode shape, $\phi_i$.

In its serial implementation, the centralized FDD method requires that a processing element
have a significant amount of memory in order to store and manipulate the output PSD matrix for
each degree of freedom in the system. Within a wireless sensing network, where memory avail-
ability is scarce, an alternative decentralized method can be used to create independent mode
shapes between sensing node pairs; a central node can then be used to combine these two-node
mode shapes into global properties after computation is complete (Zimmerman et al. 2008). In
this decentralized approach, each wireless sensor first collects a consistent set of time history
acceleration data that is converted to an FRF using an embedded FFT algorithm. Then, the
aforementioned PP algorithm is employed to look for system-wide modal frequencies. Once the
entire network is apprised of the global modal frequencies, each node can transmit its individual
FFT results at each of these frequencies to the next unit in a pre-determined chain (except the
last node in the chain, which has no successor). Using this data, each receiver node can construct
a two-degree of freedom output PSD matrix for each picked frequency using the two sets of FFT
results in its possession. Then, each pair of nodes can perform an SVD on the resulting PSD ma-
trices, extracting a set of two-node mode shapes from the singular values corresponding to each
modal frequency. Finally, all of these two-node mode shapes can be sent to a central node,
where they are recombined to form full system mode shapes. This distributed FDD technique
does produce more robust mode shapes than the PP method described above, but it requires
more wireless communication, and yet does not provide an estimate of modal damping ratios.

3.3 Random decrement

The random decrement (RD) method is built upon the concept of a “random decrement signa-
ture” (Cole 1968; Ibrahim 1977). This method states that the response of a structure due to a
random, white noise input is composed of a deterministic impulse part and a random part, which
is assumed to have zero mean. By averaging enough samples of the same input response, the
random part will average out, leaving only the deterministic impulse part of the signal. This im-
pulse response can be quickly and easily analyzed using zero crossing and logarithmic decre-
ment techniques to extract modal frequency and damping information.

Much like the PP method, this technique is easily decentralized for implementation within the
computational core of a network of wireless sensors (Zimmerman et al. 2008). This decentral-
ized approach begins with each sensor individually collecting a consistent set of time history ac-
celeration data, which is then transferred to the frequency domain using an embedded FFT. The
resulting Fourier spectrum is then filtered by removing sections outside of a modal window pro-
vided by the user (note that previous knowledge of the system’s frequency response is required
for this step). After the frequencies irrelevant to a given mode have been removed, the frequency
response at each node can be returned to the time domain using an embedded inverse fast Fou-
rier transform (IFFT). Because this modal window is specific to each mode, the RD process
must be repeated for each mode of interest. Once windowing has been completed, a summation
trigger can be used within each wireless sensor to create a number of time history “samples”
which are combined and converted into a SDOF free decay using RD averaging methods. From
the resulting decay function, zero crossing techniques can be used to extract modal frequency
information and a logarithmic decrement can be performed to extract a damping ratio estimate.
These modal parameters, which are calculated independently in each sensor, can be sent wire-
lessly to a central node, and a system-wide estimate of modal frequency and damping ratio can
be determined using statistical measures.
In order to validate the ability of a network of Narada wireless sensing units to autonomously estimate modal properties in a steel bridge, the Bandemer Park pedestrian bridge in Ann Arbor, MI is chosen as an ideal testbed. This bridge, shown in Figure 2, consists of a wooden deck supported by a simple steel truss, and is approximately 30m (100ft) long and 2m (8ft) wide. On November 27, 2007, a network of sixteen (16) Narada units were programmed with the distributed modal analysis algorithms described in Section 3 and deployed on the Bandemer Park pedestrian bridge. As displayed in Figure 3, wireless sensors were placed at consistent intervals along both sides of the deck and connected to either a PCB Piezotronics 3801D1FB3G or a Crossbow CXL02LF1Z MEMS capacitive accelerometer; both accelerometers were oriented to monitor the vertical acceleration of the bridge deck. The sensitivity of the PCB accelerometer is 0.7 V/g and its range is 3g, peak-to-peak. The sensitivity of the Crossbow accelerometer is 1.0 V/g and its range is 2g, peak-to-peak.

On the day of testing, several vibration tests were run using impulse loadings generated by a single-person (weighing 82kg) performing a heel drop. These heel drops, which are performed by quickly raising and dropping both heels simultaneously, were executed in various locations a short distance from the center of the bridge span, in an attempt to avoid exciting directly at a modal node. Because of the impulse nature of this type of loading, it can be assumed that each heel drop test applies a broadband input to the structure. An example set of acceleration time history plots collected by the wireless sensors for one of these heel drop tests can be found in Figure 4.

### 4.1 Peak picking results

In all of the test cases where a fast Fourier transform (FFT) was requested, each wireless sensor in the network was also asked to extract up to ten peaks from its individual Fourier spectrum. Because peak picking is a somewhat subjective science, no one wireless sensor can be completely relied on to accurately determine all modal peaks in the Fourier spectrum. As a result,
picked peaks from each node in the network must be sent to a centralized node or server, where system-wide results can be compiled and an intelligent decision can be made as to a possible set of system-wide modal frequencies. Figures 5a, 5b, and 5c show the Fourier spectrum calculated online in three of the Narada wireless sensors, as well as the modal peaks that each individual sensor picked within its frequency response. Figure 5d shows a periodogram of the network-wide PP results. It can be seen from this figure that while each individual sensor may not have individually determined all pertinent modal frequencies, the network as a whole did a decent job of determining all five distinct modal frequencies (3.9, 6.8, 11.6, 16.9, 20.0 Hz).

Although simplistic, the PP method is not only useful for identifying modal frequencies, but also for estimating mode shapes. The mode shapes calculated using the distributed PP method are compared with similar mode shapes calculated offline using a centralized FDD method on the wirelessly collected raw data. Both of these sets of mode shapes are plotted alongside one another in Figure 6, and are presented numerically in Table 1. All comparisons between mode shapes are formulated using the modal assurance criteria (MAC) as defined by Allemang and Brown (1983). The centralized FDD results are used as a baseline. It can be seen that the PP method performs acceptably for the higher three modes, but does not produce very accurate results for lower frequency mode shapes.
4.2 Frequency domain decomposition results

The FDD technique has several significant advantages over the PP method when estimating mode shapes from output-only response data; it not only provides more reliable and robust mode shape estimates, but it can be effectively used in systems with closely spaced modes. The mode shapes determined using the distributed FDD algorithm embedded within the network of Narada wireless sensors can be seen in Figure 6, alongside those calculated offline using the centralized FDD method and those calculated in-network using the PP technique. Table 1 provides a numerical comparison between these three methods using MAC values. It can be seen that this technique performs much better than the PP method for the low frequency modes, but is not as accurate as the centralized FDD algorithm at estimating the higher frequency mode shapes.

4.3 Random decrement results

The last embedded analysis technique used in this study is the RD method. When running RD tests in the field, a consistent set of acceleration data is first collected at each node. Using different frequency windows provided by the user (each calculated using PP results), each mode can be singled out for RD analysis. For example, a window of 3.0-5.0Hz was used to isolate mode 1 (at 3.9 Hz). At this point, each node in the wireless sensing network performs RD calculations and returns the resulting random decrement response along with an estimated frequency and damping ratio. In this way, 16 independent estimates of these two modal properties are created. A graphical example of several random decrement responses for different modes can be seen in Figure 7, and numerical estimates of modal frequencies and damping ratios found with this method can be found in Table 1. Note that because the fourth and fifth modes (17 and 20Hz) are significantly high relative to the sampling rate (100Hz), the random decrement response for these modes did not produce meaningful damping ratios or modal frequency estimates.

Figure 6. (a) Offline FDD modes, (b) embedded PP modes, and (c) embedded FDD modes.

Figure 7. Example random decrement frequency and damping ratio results for modes 1 & 2.
Table 1. Summary of modal identification results from autonomous embedded methods.

<table>
<thead>
<tr>
<th>Method</th>
<th>Natural Frequency (Hz)</th>
<th>Damping Ratio</th>
<th>MAC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mode 1 Mode 2 Mode 3 Mode 4 Mode 5</td>
<td>Mode 1 Mode 2 Mode 3</td>
<td>Mode 1 Mode 2 Mode 3 Mode 4 Mode 5</td>
</tr>
<tr>
<td>Centralized FDD (off-line)</td>
<td>3.91 6.79 11.57 16.94 20.04</td>
<td>-- -- --</td>
<td>1.000 1.000 1.000 1.000 1.000</td>
</tr>
<tr>
<td>Peak Picking (embedded)</td>
<td>3.91 6.69 11.41 16.94 20.00</td>
<td>-- -- --</td>
<td>0.141 0.969 0.886 0.944 0.589</td>
</tr>
<tr>
<td>Decentralized FDD (embedded)</td>
<td>-- -- -- -- -- --</td>
<td>-- -- --</td>
<td>0.994 0.990 0.953 0.689 0.499</td>
</tr>
<tr>
<td>Random Decrement (embedded)</td>
<td>±0.00 ±0.04 ±0.08 -- --</td>
<td>±0.12% ±0.70% ±0.04%</td>
<td>-- -- -- -- --</td>
</tr>
</tbody>
</table>

5 SUMMARY AND CONCLUSIONS

In this study, a 16 node network of Narada wireless sensing units is deployed on the Bandemer Park pedestrian bridge in Ann Arbor, MI. Using distributed versions of three common output-only modal identification methods, the wireless network is capable of autonomously determining the bridge’s modal frequencies, mode shapes, and modal damping ratios. It can be seen that these embedded techniques produce modal parameters that are comparable to those obtained using traditional offline analysis techniques. Further work is needed to extend the concepts embedded herein to other modal analysis and damage detection methods.

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