Parallel data processing architectures for identification of structural modal properties using dense wireless sensor networks

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ABSTRACT: With recent advances in wireless sensing and data acquisition technology, it has become feasible to instrument a large structure with a dense array of wireless sensors. Furthermore, the analog-to-digital conversion and data processing capabilities of current wireless sensing prototypes offer the ability to efficiently distribute data processing tasks across a large network of wireless sensing nodes. In this paper, three output-only system identification methods are modified for implementation in a distributed array of processors and embedded within the computational core of a network of wireless sensors. The embedded algorithms implemented include the peak peaking, random decrement and frequency domain decomposition methods for identification of structural modal parameters including modal frequencies, damping ratios and mode shapes. Emphasis is placed on parallel implementations of these typically centralized algorithms to ensure scalability of the approach to networks defined by high nodal densities. Using the balcony of a historic theatre as a testbed, a network of wireless sensors is installed and allowed to collect and process acceleration response data during a set of vibration tests so that modal parameters can be estimated by the network.

Keywords: Wireless sensors, system identification, parallel data processing, wireless sensing networks.

1 INTRODUCTION

In recent years, structural health monitoring (SHM) systems have become increasingly important to the civil engineering community. These systems, which utilize dense networks of sensing devices to provide estimates of structural health, not only promise to reduce the routine maintenance and inspection costs of a wide variety of structures, but may also serve to increase the level of public safety by drawing attention to potential structural problems before failure occurs. While networks of tethered sensors have already been installed in large structures around the world (Ko and Ni 2005), the high costs associated with traditional tethered monitoring systems have prevented their widespread adoption. However, wireless sensing technologies have emerged as a cost-effective alternative to traditional cable-based sensing systems. By eliminating the need for the extensive lengths of cable required to link sensors to a central data repository, these wireless devices can be deployed at reduced costs and with higher nodal densities than traditional tethered monitoring systems. Additionally, wireless sensors leverage analog-to-digital converters (ADCs) and low-power microprocessors in order to perform data processing tasks at each sensing node. As such, a large number of wireless sensor prototypes have recently been developed and validated in both the academic and commercial sectors (Lynch and Loh 2006).

A wireless sensor’s ability to autonomously collect and analyze data has led to these devices being labeled as “smart” sensors (Spencer et al. 2004). These “smart” devices have several advantages over traditional system 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. Because this processed data is typically only a fraction of the size of a raw time history record, power consumption and network bandwidth problems traditionally associated with wireless transmission can be greatly mitigated.

In civil engineering, the ability to extract modal information (modal frequencies, mode shapes, and damping ratios) from sensor data has been important for the assessment of structural performance and the calibration of analytical design models. Modal parameters have even been used to detect and locate severe structural damage in the wake of natural events such as earthquakes (Doebling et al. 1998). Because
it is often difficult to excite a large civil structure in a controlled manner with measurable input excitation forces, modal parameter estimation techniques using only output response data have been utilized in lieu of traditional input-output methods. These techniques have gained even more popularity as recent advances in low-cost wireless sensing technology has made dense instrumentation of large civil structures possible.

In this paper, three output-only modal identification techniques are adopted and modified for use within a distributed wireless sensing network: the simple 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 drawing on parallel processing techniques to 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 theatre in southeastern Michigan is instrumented with a dense network of wireless sensing prototypes. Over the span of several vibration tests, each of the distributed modal identification techniques is used to determine modal properties of the system. For validation, the results from the embedded algorithms are compared with similar modal analysis techniques run off-line using time history data recorded by the wireless network.

2 WIRELESS SENSOR HARDWARE

In this study, a wireless sensor prototype designed by Wang et al. (2005) is adopted. This sensing unit, shown in Figure 1, relies on the 900 MHz Maxstream 9XCite wireless transceiver for wireless communication. This radio is low power and can transmit over distances of up to 300m. The computational core of the sensing unit is driven by an 8-bit Atmel AVR ATmega128 microprocessor. This versatile chip has 128 kB of flash memory (ROM), 4 kB of RAM, and can run at clock speeds of up to 8 MHz. An additional 128 kB of external memory is used to supplement the data storage capacity of the microprocessor, allowing for the storage of up to 64,000 data points at one time. The unit’s sensing interface consists of a four channel, 16-bit Texas Instruments ADS8341 ADC. This prototype employs five AA batteries to provide a constant DC supply voltage offering an operational life expectancy of approximately 30 hours. By using beacon timing to synchronize at the time of data collection, synchronization has been shown to be better than 5ms in large networks utilizing these sensor prototypes (Lynch et al. 2006).

The wireless sensing prototype used in this study has been validated extensively on a variety of bridges around the world. For example, Lu et al. (2006) installed a network of 9 wireless sensing units on the Gi-Lu cable-stayed bridge in Taiwan while Lynch et al. (2006) installed 14 wireless sensors on the Geumdang bridge in Korea. In both of these cases, wirelessly collected data provided accurate results which could be validated against a cable-based data acquisition system; such tests show the validity of this wireless sensing prototype for data acquisition in large-scale civil structures.

3 DISTRIBUTED MODAL IDENTIFICATION ON A NETWORK OF WIRELESS SENSORS

In general, it is very difficult to excite a large civil structure in a controlled manner. As a result, several output-only methods have been commonly adopted for 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 peak picking method (Ewins 1986), the frequency domain decomposition technique (Brincker et al. 2001), and the random decrement method (Cole 1968; Ibrahim 1977). To the author’s knowledge, this is the first time these methods have been implemented within a wireless monitoring system for automated in-network execution.

3.1 Peak picking

The peak picking (PP) method is the simplest known technique for estimating the modal properties of a structure from system output data. This method is based on the fact that the frequency response function (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. If a structure is lightly damped with 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, \( \phi_i \).

This method is relatively easy to decentralize and implement in a wireless sensing network. First, a consistent set of acceleration time history data is collected at each sensing node and converted to an FRF using an embedded version of the fast Fourier transform (FFT) algorithm. Each node then picks the largest peaks from its frequency response 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. Because some sensing nodes may not be capable of detecting peaks at all modal frequencies due to positioning, it is necessary to transmit peak information to a central node that can view the individual PP results for the entire network as a whole. By tabulating the periodicity at which a given frequency has been picked by nodes on a network, this central node infers a subset of reasonable modal frequencies from the original PP data. This node then shares these system-wide modal frequencies with the rest of the wireless sensors, each of which then broadcast the imaginary components of their respective FRF at the picked frequencies to the rest of the network. This sharing of data provides all sensing nodes with mode shape information.

This decentralized method is advantageous because it is relatively simple to implement and it drastically limits the amount of bandwidth required to determine in-network modal frequencies and mode shapes relative to a centralized setting. However, peak picking does not properly handle closely spaced modes, and can not provide adequate damping estimates. As such, two additional methods are proposed that make modal identification using a wireless sensing network much more robust.

### 3.2 Frequency domain decomposition

The frequency domain decomposition (FDD) technique, developed by Brincker et al. (2001) 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, allowing close modes to be identified with high accuracy. In this method, an estimate of the output power spectral density (PSD) matrix, \( \hat{G}_{yy}(j\omega) \), is 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. Singular values and singular vectors can then be extracted from the output PSD by taking the SVD of the matrix \( \hat{G}_{yy}(j\omega) \). 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, \( \mathbf{u}_{i1} \), can be interpreted as an accurate estimate of the mode shape, \( \phi_i \).

Unfortunately, because of the need to store and manipulate the output PSD matrix for each degree of freedom in a system, 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 memory available at each sensing node, a decentralized method is alternatively proposed and implemented in this study.

In this decentralized FDD approach, the wireless sensing network first collects a consistent set of time history acceleration data and converts it to the frequency domain using an embedded FFT. Then, the aforementioned embedded PP algorithm is employed to look for system-wide modal frequencies. Once these results have been shared with each node in the network, every unit transmits its FFT results to the next unit in a pre-determined chain (except the last unit in the chain, which has no successor). Using this shared data, all but one of the sensing nodes constructs a two degree of freedom output PSD matrix using two sets of FFT results. After performing an SVD on this PSD matrix, each of these nodes extracts a set of two-node mode shapes from the singular vectors corresponding to each modal frequency. Finally, all two-node mode shapes are transmitted back to a central node, where they are recombed to form full system mode shapes.

Because of the need to share large amounts of data between nodes, this approach requires significantly more wireless communication than the decentralized PP method. However, a significant improvement in communication draw can be made by broadcasting FFT information from one node to the rest of the network instead of transmitting that information individually from node to node. This streamlined method minimizes wireless data transfer, but could encounter issues such as transmission range limits and possible data loss. Regardless, distributed FDD analysis does provide much more reliable and robust mode shape estimates than does the PP method. Additionally, because all FFT and SVD computation is performed simultaneously in a parallel fashion, significant time savings can be realized from the parallel environment with this method scalable to an almost infinite number of nodes. However, the distributed FDD technique can not provide damping ratio estimates that are as reliable as those obtained through a centralized FDD. As such, an additional method is presented that can extract relatively accurate estimates of modal damping ratios from a distributed array of wireless sensors.
3.3 Random decrement

The random decrement technique is based upon the concept of the “random decrement signature,” proposed initially by Cole (1968), and explored in greater detail by Ibrahim (1977). This concept essentially states that the response of a structure due to a random 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 random response, the random part will average out, leaving only the deterministic part of the signal.

In this study, a distributed RD algorithm is designed and embedded within the computational core of a network of wireless sensors. 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 this data to the frequency domain using an embedded FFT. Employing a frequency window provided by the user, 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 separately for each mode. At this point, a summation trigger is used within each sensing node to create a number of samples which are combined and converted into a SDOF free decay using RD averaging methods. Modal frequency and damping information are then automatically extracted from the response by utilizing zero crossing and logarithmic decrement techniques. These modal parameters, which are calculated in each node in the network, are sent wirelessly to a central node where a system-wide modal frequency and damping ratio are determined using statistical measures and broadcast to the network.

Much like the embedded PP method, this decentralized RD technique is rather simple to implement on a wireless sensing network. It also provides accurate estimates of modal frequencies and damping ratios by taking advantage of the great degree of redundancy available within a sensing network, and does not require as much communication as would be necessary in the centralized setting. However, this method is not suited to determining modal properties involving closely spaced modes, and in a multiple degree of freedom system prior knowledge of the frequency characteristics of the system is required in order to properly window the Fourier spectrum (such information could be autonomously determined using the embedded PP algorithm).

4 EXPERIMENTAL TESTBED AND RESULTS

A historic theatre, located in southeastern Michigan, is selected as an appropriate structure to validate the embedded algorithms proposed in this study for use within a wireless sensing network. The main auditorium balcony is chosen for instrumentation purposes. This balcony is approximately 50m (150ft) wide, and is structurally supported only at the rear and sides of the theatre.

On February 2, 2007, the front section of the main balcony (specifically the first five rows within a 3m (15ft) band of the balcony edge) was instrumented using the wireless monitoring system described in Section 2. Twenty-one (21) wireless sensing units were installed in a seven-by-three grid, with seven units distributed evenly across the span of the balcony in each of rows 1, 3, and 5. The location and distribution of these sensing units is shown in Figure 2a. Attached to each wireless sensing unit was either a PCB Piezotronics 3801D1FB3G MEMS capacitive accelerometer or a Crossbow CXL02LF1Z MEMS capacitive accelerometer 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.

On the day of testing, a set of fifteen nearly identical tests were run using impulse loadings generated by a single-person (weighing 82kg) performing a heel-drop. This type of loading is performed by quickly raising and dropping both heels simultaneously. The objective of these tests was to validate the ability of the proposed distributed modal identification methods to accurately determine the bal-
conson’s modal parameters (modal frequencies, damping ratios, and mode shapes) using the embedded processing capabilities residing on a spatially distributed network of wireless sensor nodes. Results from each of the three methods proposed in this study were obtained and compared against results from an offline centralized FDD analysis.

4.1 Peak picking results

In all of the testing cases in which PP methods were used, each wireless sensor in the network was asked to extract the three highest peaks from the Fourier spectrum created using an 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 central node or server, where an intelligent decision can be made about final modal frequencies. PP results from one wireless sensor can be seen in Figure 3b. Figure 3c shows the ability of a central node 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 network-wide PP results as a whole, a reasonable estimate of global peak frequencies can be made. Note that the third mode (5.11 Hz) is absent, as the chosen excitation point did not provide adequate spectral content at this frequency for proper PP mode detection. Modal frequencies and mode shapes calculated using the decentralized PP method are compared with modal information calculated using an offline centralized FDD method and presented in Table 1. All mode shape comparisons are made using the modal assurance criteria (MAC), as defined by Allemang and Brown (1983).

4.2 Frequency domain decomposition results

The FDD 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 that can be easily assembled by a central node or server. Figure 4 displays four mode shapes identified using this decentralized FDD technique, and compares them with mode shapes identified using the decentralized PP method (determined by the wireless sensor network) as well as an offline centralized FDD method. Table 1 provides a numerical comparison between mode shapes calculated using the embedded FDD method and those calculated offline. Again, these comparisons are made using MAC values.

4.3 Random decrement results

For each test in which the RD method was used, a consistent set of time history data was transformed at each node into a SDOF free decay response func-
tion using a user-defined trigger amplitude and frequency window meant to target a specific mode (e.g. 2.0-3.5 Hz for mode 1). Figure 5 shows a complete output response time history alongside an RD free decay response function calculated by wireless sensor 4 (while windowing mode 1). It can be seen that by employing zero crossing and logarithmic decrement techniques on the resulting free decay response function, an estimate of modal frequency and damping can be determined at each sensing location. The type of quality result seen in Figure 5 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 averaging the results. System-wide frequency and damping results obtained using the distributed RD method are compared with results obtained using a centralized FDD method and are displayed in Table 1.

5 SUMMARY AND CONCLUSIONS

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. A 21-node wireless monitoring system was deployed on the balcony of a historic theatre in southeastern Michigan. This wireless network was able to autonomously determine modal frequencies using a distributed peak picking algorithm, mode shapes using a distributed frequency domain decomposition method, and modal damping ratios using a distributed random decrement technique. It can be seen that the embedded methods proposed in this paper 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. Further research is 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.

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