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Decentralized Output-only Modal Identification Techniques for Wireless Monitoring Systems

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ABSTRACT

Sensor network technology entails the deployment of small, low-power sensor nodes that can communicate with one another. Since sensor networks can be used to monitor the condition of many types of architectural spaces, the technology has recently received significant academic and industrial attention. Amongst the potential applications, structural monitoring of large-scale civil structures is one of the most promising. With the recent advancement of low-cost and ultra-compact wireless sensing and data acquisition technologies, it has become feasible to apply dense arrays of wireless sensors in a single structure so as to identify its structural properties. In many cases, forced excitation of a civil structure in a controlled manner is difficult, especially when the size of the structure increases. Therefore, output-only modal identification methods are advantageous for use in characterizing system properties. This paper describes three output-only modal identification methods (peak picking, random decrement, and frequency domain decomposition) embedded in dense wireless sensor networks. The embedded software is designed using a decentralized computing architecture; such an approach is quite different from conventional centralized structural monitoring systems where algorithms are implemented in a centralized, but resource-rich data server. The decentralized computing architectures proposed in this work are scalable to a large numbers of sensors organized as a community that collectively carries out complex engineering analyses. Using the cantilevered balcony of a historic theatre as a test-bed structure, an array of twenty-one wireless sensors are deployed to collect acceleration response data during a series of vibration tests. The proposed algorithms for wireless sensors are effective in autonomously determining the balcony's modal properties (including natural frequencies, modal damping ratios, and mode shapes).

INTRODUCTION

Structural health monitoring (SHM) has attracted wide-spread attentions in recent years leading to high expectations for this technology. In Japan, there are three motivations driving the development

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of this technology: (1) public demand for technologies that can automatically diagnose the health of structures after a large earthquake; (2) the necessity of society to continue its use of old buildings and infrastructures which were built during period of high economic growth in Japan; (3) commercial demand for more quantitative evaluation of structural performance during due diligence in real estate transactions. Within the field of SHM, wireless sensors have emerged as a viable data acquisition technology offering cost lower than traditional wired monitoring systems. Wireless sensor nodes consist of three major functionalities: sensing, networking, and computing. In this study, an emphasis is placed on the computing functionality of the wireless sensors. Specifically, the present study is intended to modify widely employed modal identification methods so they can be implemented in a decentralized fashion upon wireless sensor networks. Three modal identification methods are explored: peak-picking, random decrement, and frequency domain decomposition methods. The decentralized modal identification methods as executed by a wireless sensor network are demonstrated during experimental testing of a historical theatre balcony.

DECENTRALIZED SHM USING SENSOR NETWORKS

Structural health monitoring strategies can be broadly classified into two categories: global and local monitoring. The global monitoring method focuses on the existence, or degree of damage present in the whole structure. In contrast, local monitoring methods are applied to pre-identified probable damaged locations (“hot spots”) for accurate long-term inspection. In the global monitoring methodology, structural condition is evaluated mainly by identifying and detecting the variance of mathematical model parameters (e.g., modal features) which express the global behavior of the structure. Most of the current global monitoring systems are designed based on conventional seismic observation systems, which are centralized systems gathering analog data from multiple acceleration meters via high-cost coaxial cables (Celebi 2002). In such a system (see Fig. 1a), data is also analyzed at the central data server. Large-scale systems suffer from complex installations and high costs. In addition, an excessive amount of data is concentrated at the data server; in many instances, the data is simply stored and left for future manual investigation by engineers.

Over the last few years, many researchers have published detailed studies on sensor network technology which can be applied for system identifications and damage detections in civil structures (Lynch *et al*. 2006). Some of the weak points mentioned above for conventional SHM systems are resolved by making use of the best features of sensor networks. For example, decentralization of processing power allows data to by autonomously processed on the sensor nodes. Also, wireless communication eradicates any need for wiring in the structure which lowers system costs (see Fig. 1b). As a result of these features, sensor networks will be able to achieve more scalable monitoring systems defined by higher sensor densities. High sensor densities are desirable when applying the technology to large structures such as buildings and bridges. These high densities are driving innovation in how future monitoring system are deployed. For example, if the number of sensors increases by two or three times, the advantage gained is simply a greater amount of data available. However, if the number of sensors increases 10 or 20 times, then new system architectures would be necessary to extract detailed information from such vast sources of sensed data. While high sensor densities would permit the measurement of local structural responses, centralization of the monitoring system is not technologically possible. Rather, decentralized data processing architectures are needed to

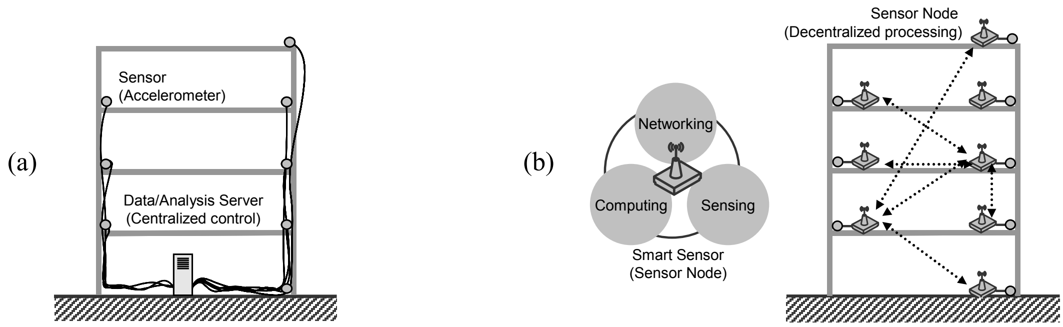


Fig. 1. Global monitoring system:
(a) conventional centralized system; and (b) decentralized system with sensor networks

process data in-network and to minimize communication of raw sensor data using the limited bandwidth wireless communication channel. With this view of the future in mind, this study explores decentralization of three traditional modal identification algorithms for in-network execution in high density wireless monitoring systems. The algorithms introduced are embedded in low-cost wireless sensor prototypes and experimentally validated in a full-scale structure.

DECENTRALIZED SYSTEM IDENTIFICATION METHODS

There are many unique challenges when attempting to realize large-scale SHM using wireless sensor networks: limited computation resources at a given sensor, limited memory capacity, limited communication bandwidth between sensors, and difficulties in the controlled excitation of large-scale structures. These challenges ultimately shape how embedded data processing algorithms are to be embedded within wireless sensors for network execution. Specifically, this study considers the challenges when implementing three of output-only modal identification methods for embedment in a wireless sensor network: the peak picking (PP) method, the random decrement (RD) method, and the frequency domain decomposition (FDD) method (Brinker *et al*. 2001, Tamura *et al*. 2002). As shown in Fig. 2, the modal frequency, f_i, is identified by PP or RD methods. Damping factors, ξ_i, and mode shapes, ϕ_i, are calculated by RD or FDD methods. Before illustration the operation of these three embedded processing methods, their implementation is briefly described. The computing associated with these output-only identification methods is divided into two types. First, calculations that can be performed at a specific sensor using only that sensor's data is defined as Type I calculations. Once data has been locally processed at each sensor, the intermediate results are partially shared between nodes resulting in further community-wide processing; this community-based processing is termed Type II processing.

Type I: Data processing at a single sensor

The PP and the RD methods are categorized as Type I algorithms. For example, each sensor node processes its own time-series data locally, and then sends the analysis results to a special designated node or the central data server. Once global modal parameters are shared between all of the sensors, a consensus can be formed to define the global modal parameters of the structure.

The PP method determines the modal frequency, f_i, by conducting a peak search of Fourier spectra of measured data. The sensor nodes can determine the Fourier spectra using an embedded Fourier transform algorithm (*i.e.*, FFT). PP is a well known frequency domain techniques that is considered simple to implement and easy to understand.

The RD method is a time domain technique that is widely used for damping estimation with micro-tremor recordings. The RD method is essentially an averaging procedure of time series data resulting in a smoothed free vibration decayed response of the structure. From this free response function, the modal frequency, f_i, is determined by precisely timing a zero crossings. The damping ratios, ξ_i, can be estimated using the logarithmic decrement of the decay function's amplitude peaks. While a band-pass filtering is necessary to isolate a targeted mode, the RD implementation is straightforward using FFT and IFFT algorithms embedded in the sensors.

Type II: Community processing by combining multiple points of sensor data

The FDD method is one of the modal identification techniques using data sets of sensors defined at multiple points on the structure. Having spatial diversity in the data set allows for the determination of mode shapes of the structure. An advantage of the FDD method is its ability to resolve closely spaced modes. The FDD method estimates modal parameters by singular value decomposition (SVD) of a power spectral density (PSD) matrix composed of sensor data from multiple sensors. However, because of the need to manipulate the PSD matrix whose dimension is the number of degrees-of-freedom of the structure, the method is not well suited for implementation in sensor nodes as it is currently conceived. An alternative implementation is proposed where calculations are decentralized across the sensor network.

The defining feature of the decentralized FDD method implemented in this study (see Fig 3), is the decomposition of the multi-degree-of-freedom system into a redundant set of two-degree-of-freedom

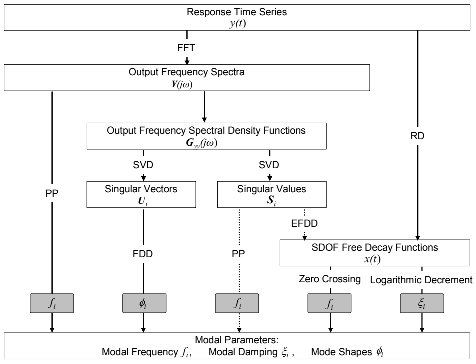


Fig. 2. Decentralized modal identification methods (implement parts of solid lines)

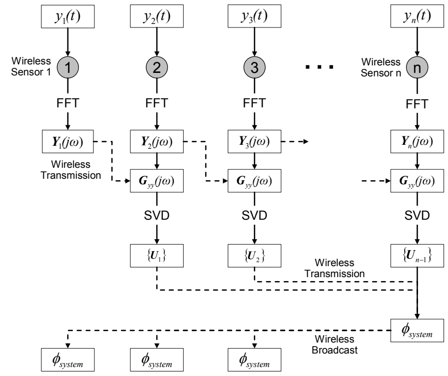


Fig. 3. Decentralized FDD method

systems. Given spatial overlap of the two-degree-of-freedom systems, the global modes can be recomposed by stitching two-point modes together. First, every sensor node acquires an acceleration response, $y_n(t)$, synchronously. Next, the node converts it to frequency domain by the embedded FFT, and transfers the FFT result, $\boldsymbol{Y}_n(j\omega)$, to the next node according to a pre-determined topology. Then, each node composes the PSD matrix, $\boldsymbol{G}_{yy}(j\omega)$, from two sets of the FFT results. After each sensor node executes an SVD on the two-by-two PSD matrix at the modal frequency, ω_i, two-node mode shapes, ϕ_i, are extracted from the first singular vector, $\boldsymbol{U}_1$. Finally, all two-node mode shapes are combined to form the global mode shape, ϕ_{system}, of the whole structure.

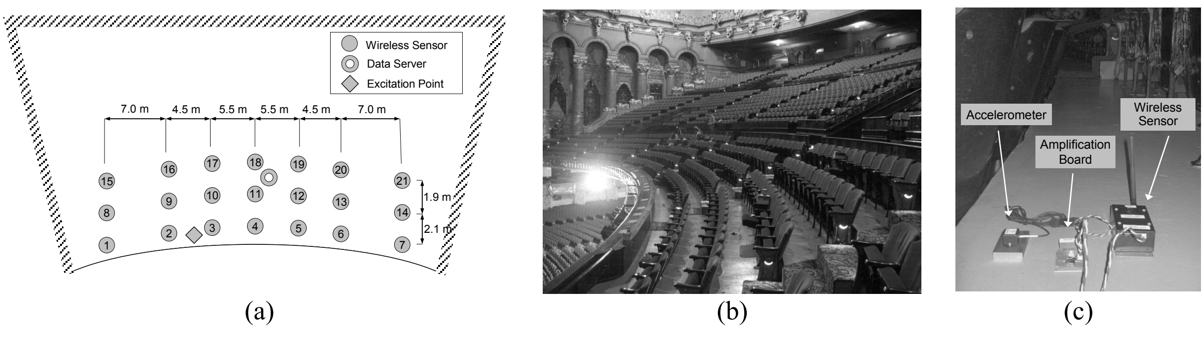
DEMONSTRATION EXPERIMENT

Wireless sensing system prototypes

In this study, the proposed algorithms were implemented upon the wireless sensing system proposed by Lynch *et al.* (2006). This system consists of sensor nodes, a gateway node, and a PC (data server) connected to the gateway. Each sensor node has four external sensor input terminals to which sensors like accelerometers can be interfaced. A 16-bit analog-to-digital (AD) converter on the sensor node can acquire data at rates as high as 100 kHz. An 8-bit CPU and 128 kB RAM on the sensor nodes enables a local data processing. A 900 MHz radio may transfer the processed data to other nodes or the gateway node.

Experimental testbed

Using a cantilevered balcony of a historic theatre as a test-bed structure, an array of twenty-one sensor node prototypes was deployed for a demonstration experiment, as shown in Fig. 4. The time required for sensor deployment was only 1.5 hours which is one of the big advantages of wireless sensing. Capacitive MEMS accelerometers were attached to each sensor node to record the balcony floors vertical vibration at a 50 Hz sampling. For this study, a rough impulsive loading was generated by a simple heel-drop method (quickly dropping both heels simultaneously). The location of heel-drop excitation was between the sensors #2 and #3 in Fig. 4a. After data collections, every sensor node processes the data locally and estimates modal parameters.



(a) (b) (c)

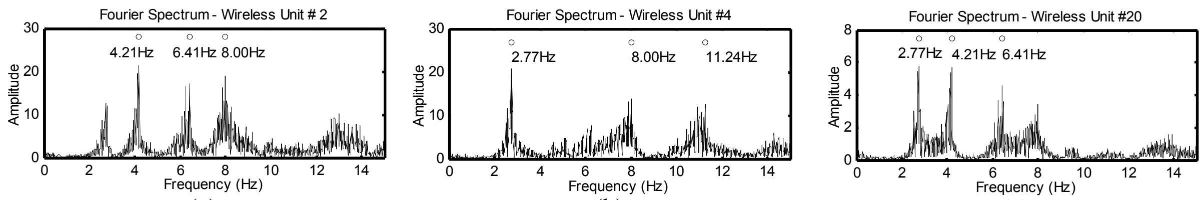
Fig. 4. Experimental setup: (a) layout of instruments; (b) cantilevered balcony of theatre; and (c) typical set up of wireless sensor

Experimental results

The estimation results by the PP method are shown in Fig. 5. Fourier spectra executed in sensor nodes #2, #4, and #20, along with the peak frequencies picked by the PP method, are plotted in these graphs. Peaks of the second (4.2 Hz) and the fourth modes (6.4 Hz) are clearly seen in nodes #2 and #20, but not clearly in #4. On the other hand, the peak of the first mode (2.8 Hz) is large at nodes #4 and # 20, but small at #2. These results indicate that a high-density sensing by sensor networks provides reliable estimations of modal parameters, even for identification of higher vibration modes. Note that the third mode is missed because the excitation point corresponds to a node of the third mode shape.

Next, the estimation results by the RD method are shown in Fig. 6. Fig. 6a displays the random decrement response in the first mode at node #4, and modal frequency and damping estimated from this response. Fig. 6b is the second mode result at node #6. The embedded band-pass filter was applied to the time-series data before calculating the RD response in the sensor nodes: the frequency window of the filter is ranging from 2.0 Hz to 3.5 Hz for the first mode identification and from 3.5 Hz to 4.5 Hz for the second mode. It should be noted that the envelope curves in the plots, which are calculated theoretically from the estimated modal frequency and damping ratio, correspond well to the calculated RD responses.

Then, the results of identification for the FDD method are presented. Three different network topologies were designed and applied to the experimental tests of the decentralized FDD method. In Topology 1, adjacent two nodes share Fourier spectra and create two-node mode shapes. In Topology 2, every other node shares Fourier spectra while in Topology 3, each node shares data with the third node closest to it. Mode shapes are calculated off-line to serve as reference; these modes were calculated by the conventional centralized FDD method and are illustrated in Fig. 7a. Online-estimated mode shapes by the decentralize FDD method are shown in Figs. 7b, 7c, and 7d.



(a) (b) (c)

Fig. 5. Estimation results by the PP method: (a) node #2; (b) node #4; and (c) node #20

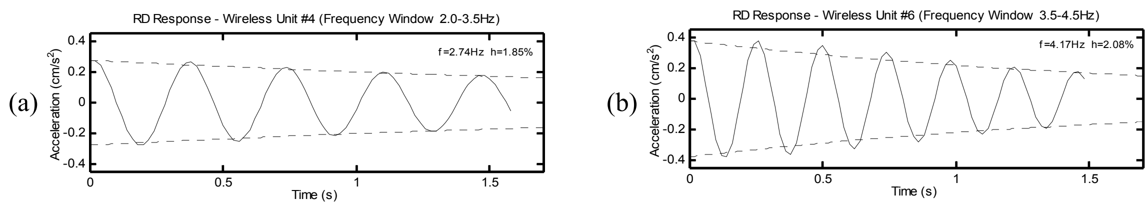


Fig. 6. Estimation results by the RD method: (a) first mode; and (b) second mode

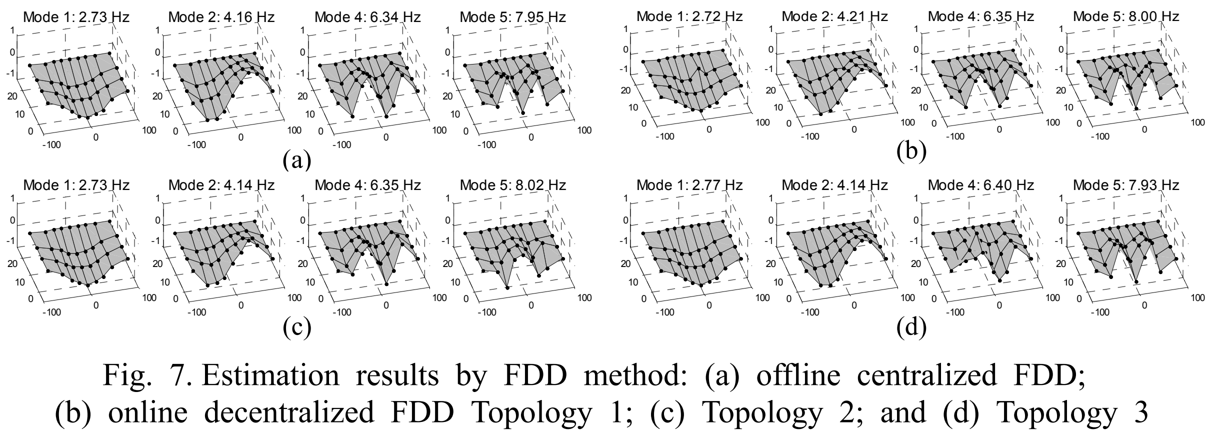


Fig. 7. Estimation results by FDD method: (a) offline centralized FDD; (b) online decentralized FDD Topology 1; (c) Topology 2; and (d) Topology 3

Table 1. Summary of modal identification results

		Natural Frequency (Hz)				Damping Ratio (%)		MAC			
	Run #	Mode 1	Mode 2	Mode 4	Mode 5	Mode 1	Mode 2	Mode 1	Mode 2	Mode 4	Mode 5
Centralized FDD (off-line)	1	2.734	4.163	6.335	7.946	2.321	1.610	1.000	1.000	1.000	1.000
Peak Picking (embedded)	2	2.727	4.210	6.349	7.996	-	-	-	-	-	-
	3	2.734	4.135	6.342	8.020	-	-	-	-	-	-
	4	2.772	4.144	6.396	7.929	-	-	-	-	-	-
Random Decrement (embedded)	8	2.740	-	-	-	1.792	-	-	-	-	-
	9	-	4.159	-	-	-	1.864	-	-	-	-
Decentralized FDD (embedded)	5	-	-	-	-	-	-	0.957	0.985	0.961	0.840
	6	-	-	-	-	-	-	0.988	0.943	0.821	0.373
	7	-	-	-	-	-	-	0.994	0.984	0.630	0.960

These plots indicate that the proposed decentralized FDD method was effective in achieving appropriate mode shape estimation comparable with the conventional centralized method, except for some examples of higher modes in Topology 2 and 3.

Table 1 shows the summary of estimation results by all of the identification methods in this study. The modal frequencies and damping ratios by the PP or RD methods in this table is based on averaging the results from all of the sensor nodes. Notice that all of the estimation results of modal frequencies correspond to the reference value by the centralized FDD method. The estimation results of mode shapes by the decentralized FDD are evaluated using the MAC (Modal Assurance Criteria) with the centralized FDD modes serving as the reference set of modes. As most of the MAC values are 0.9 or greater, it is confirmed that the mode shapes were identified with high accuracy.

SUMMARY AND CONCLUSION

In this study, three output-only modal identification methods (peak picking, random decrement, and frequency domain decomposition) were modified in a decentralized fashion for embedment within wireless sensor network prototypes. The wireless sensing system with 21 sensor nodes was installed in a cantilevered balcony of a historic theatre to determine its modal properties. The estimation results by the proposed decentralized methods were equivalent to the results of the conventional centralized method. Therefore, the effectiveness of decentralized modal identification on sensor networks was confirmed.

With rapid advancements of performance and price-reduction of sensor networks, high-density and large-scale installations will be increasingly more practical in large civil structures. Furthermore, the scalable decentralized modal estimation methods presented in this study would be effective in mining raw time history data for information regarding the properties of the structure. Other computational methods are possible for embedment, including damage detection algorithms; such algorithms are currently being explored for implementation in wireless structural monitoring system.

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