Embedment of structural monitoring algorithms in a wireless sensing unit

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(Received October 4, 2002, Accepted February 11, 2003)

Abstract. Complementing recent advances made in the field of structural health monitoring and damage detection, the concept of a wireless sensing network with distributed computational power is proposed. The fundamental building block of the proposed sensing network is a wireless sensing unit capable of acquiring measurement data, interrogating the data and transmitting the data in real time. The computational core of a prototype wireless sensing unit can potentially be utilized for execution of embedded engineering analyses such as damage detection and system identification. To illustrate the computational capabilities of the proposed wireless sensing unit, the fast Fourier transform and auto-regressive time-series modeling are locally executed by the unit. Fast Fourier transforms and auto-regressive models are two important techniques that have been previously used for the identification of damage in structural systems. Their embedment illustrates the computational capabilities of the prototype wireless sensing unit and suggests strong potential for unit installation in automated structural health monitoring systems.

Key words: structural health monitoring; damage detection; time-series analysis; wireless monitoring; wireless sensing unit; structural monitoring; auto-regressive modeling.

1. Introduction

The concept of structural monitoring is not new to the field of structural engineering. For example, to monitor the response of bridges during seismic responses, the California Department of Transportation since 1977 has instrumented 61 long span bridges with over 900 permanent sensors (Hipley 2001). The majority of monitoring systems installed have been widely used to assess the performance of structures, particularly during seismic disturbances. Other applications have included permanent installation of sensors in structures for structural control as well as temporary installation for identifying the modal properties of a structure. Current commercial monitoring systems are characterized by hub-spoke architectures with distributed sensors connected to centralized data servers through cables. Unfortunately, the costs associated with cable-based monitoring systems are high due to expensive installation and maintenance efforts.

Revolutionary advances in the commercial embedded systems market are driving innovation in

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many engineering fields. By utilizing advanced embedded system technologies, a novel structural monitoring system can be created as a low-cost alternative to current tethered systems in addition to providing a broader set of performance features. The combination of advanced microcontrollers, analog-to-digital converters and wireless radios for the creation of wireless sensors has been explored by both academia and industry. Academic research has produced innovative wireless sensing systems (Warneke and Pister 2002 and Min *et al.* 2001). Development efforts have also resulted in some commercial vendors offering wireless sensing platforms with diverse performance specifications. Our research focuses on the unique demands of the structural engineering community such as the need for low-power consumption and long communication ranges that warrant the design of a wireless sensing platform optimized for structural monitoring.

In particular, structural monitoring systems can greatly benefit from wireless communications and low-cost microcontrollers. Straser and Kiremidjian (1998) explored the design of a wireless structural monitoring system comprised of wireless sensing units. Their work eradicated the need for extensive cabling by using wireless communications for the transfer of sensor measurements in a wireless sensor network. Lynch *et al.* (2002) has extended the design of the wireless sensing unit to include microcontrollers that embody computational power for data interrogation tasks. The coupling of computational power with each sensor represents a significant paradigm-shift from monitoring system architectures that employ centralized data processing. Allowing sensors to locally interrogate their own data advantageously reduces the use of the wireless communication channel, thereby saving power and preventing channel inundation. Engineering analyses, such as damage detection and system identification, can be embedded in each wireless sensing unit for local execution.

Different from seismic monitoring where quantitative records of structural performance during seismic events are obtained, structural health monitoring is a monitoring methodology intended to continuously assess a structural system for identification of damage. In civil structures, the identification of damage before critical failure is of extreme importance. Structural health monitoring systems envisioned for future deployment would be fully autonomous systems comprised of two main components: first, a dense network of low-cost sensors for continuous ambient and extreme-event monitoring and second, reliable damage detection algorithms used to determine the existence, location and severity of damage. The proposed wireless sensing units represent a potential monitoring infrastructure and can be a first step towards an automated structural health monitoring system.

This study explores the hardware and software design of a wireless sensing unit capable of executing embedded engineering analyses. With computational power included, the intended application of the proposed wireless sensing units is for adoption in future structural health monitoring systems. To illustrate the potential of the sensing units in structural health monitoring systems, the fast Fourier transform (FFT) and auto-regressive (AR) time series modeling are implemented and validated using recorded sensor measurements from a five-story laboratory test structure. While FFT and AR analyses have both been used in damage detection approaches, this study does not use them for the diagnosis of damage in the chosen test structure. Rather, the focus of the study is to illustrate the computational capabilities of the wireless sensing units.

2. Hardware design of the wireless sensing unit

The hardware design of the wireless sensing unit proposed by Lynch *et al.* (2002) can be divided into three basic modules: the sensing interface, the computational core, and wireless communications. The sensing interface is responsible for the acquisition of measurement data from sensors connected to the unit. The interface is sensor transparent allowing any analog sensor to interface to the unit. While accelerometers are a popular choice among structural engineers, other sensors such as strain gages, linear displacement transducers and thermometers can be easily employed. Within the sensing interface is a Texas Instruments ADS7821 single channel 16-bit analog-to-digital (A/D) converter. The converter is responsible for the conversion of analog sensor readings to a digital form. The sampling rate of the A/D converter is variable and can be adjusted by the computational core to rates as high as 10 kHz.

Microcontrollers are an important part of the sensing unit's design and serve as the computational core. Their role is to operate the entire sensing unit including the control of the A/D converter and the wireless modem. Furthermore, the computational core is responsible for the implementation of algorithms intended for damage detection, modal analysis or other applications. A unique dual-processor core design is pursued for the wireless sensing unit. First, an inexpensive 8-bit microcontroller with low power consumption characteristics is selected for the general operation of the wireless sensing unit. The Atmel AVR AT90S8515 RISC 8-bit microcontroller is chosen for this prototype because it contains serial ports, timers, multiple input/output ports and sufficient memory for program storage (8 Kbytes of ROM and 512 bytes of RAM)[1]. The low-power feature of the AVR microcontroller is important for ensuring the unit's battery (a likely portable power source) is not rapidly depleted. Second, a 32-bit PowerPC microcontroller is selected to serve as the computational workhorse of the wireless sensing unit. Supporting fast floating-point operations in hardware and having plenty of ROM and RAM memory, the Motorola MPC555 PowerPC serves as a suitable choice balancing computational power with moderate power consumption characteristics[2]. The MPC555 internally contains 448 Kbytes of flash ROM for application software and 26 Kbytes of RAM for data storage. During normal data collection activities, the PowerPC microcontroller is kept off. Only when extensive data analysis is required is the MPC555 microcontroller turned on by the 8-bit microcontroller.

Responsible for communication between each wireless sensing unit and the sensing network, Proxim RangeLAN2 wireless modems are chosen[3]. Communicating in the 2.4 GHz, unlicensed FCC radio band, the RangeLAN2 modems can communicate at ranges as high as 300 meters in open space. Depending on the building construction, this range is reduced to distances as low as 150 meters when used indoors. Using direct sequence spread-spectrum modulation, a reliable communication link can be established that is immune to narrow band interference and multi-path fading.

The completed prototype wireless sensing unit is illustrated in Fig. 1. To house the selected components, a two-layer printed circuit board is designed and fabricated. The size of the current prototype when fully assembled is about 260 cubic centimeters with components costs totaling only a few hundred dollars. Further improvements on both the form factor and cost are possible.

The sensing unit is powered by a simple 9V direct current (DC) power source such as a battery. By selecting energy-dense battery cell chemistries, a continuous battery life of over 15 hours can easily be attained (Lynch 2002). For most applications, a significantly longer battery life can be

[1]http://www.atmel.com/products/avr/
[2]http://e-www.motorola.com
[3]http://www.proxim.com/products/all/rangelan2/index.html

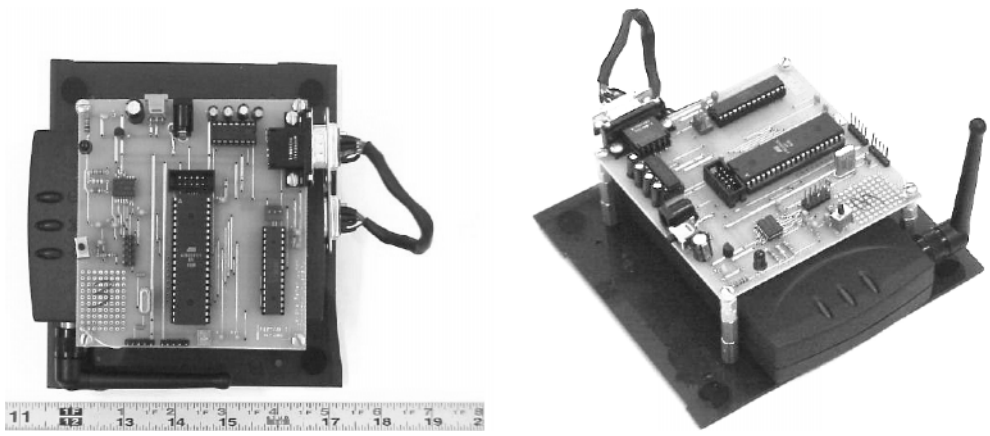

Fig. 1 Wireless sensing unit prototype

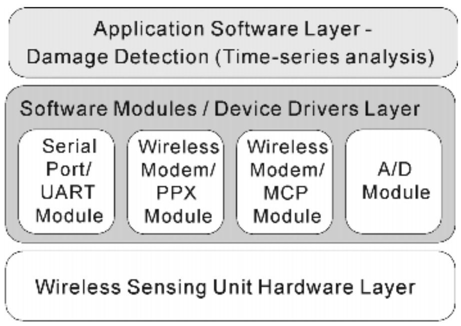

Fig. 2 Hardware, device-driver modules, and application software layers

attained through duty-cycle usage of the wireless sensing unit. If battery lives on the order of years are required, power scavenging technologies can be considered that derive power from the sun, wind or even ambient structural vibrations (Meninger *et al.* 2001).

3. The hardware-software interface

With the wireless sensing unit designed and manufactured, software is required for its operation. As shown in Fig. 2, the design of embedded software is divided into two layers: the device driver layer and the application layer. Software that interfaces with hardware is the lowest layer of software abstraction. Its role is to operate and control the unit's hardware and to assist upper software layers in accomplishing their computational goals. The functionality envisioned suggests that the layered software structure could be complex and lengthy. To ensure an efficient development process that will yield portable code of high quality, a modular software design approach is emphasized. The system software is decomposed into modules that are often referred to as device drivers.

Four software modules, written using a high level programming language such as C, are designed for control of the unit's hardware. The first module is used to control the microcontroller's serial port for sending data in a serial fashion (one bit at a time). Control of the serial port is done by controlling the computational core's universal asynchronous receiver/transmitter (UART). Functions are provided in the module for initialization of the UART at a specified transmission speed (baud rate) and for transmission and reception of bytes through the serial port.

By operating the RangeLAN2 in packetized mode, the computational core has full control over the configuration and operation of the modem through the serial port. Two other modules are designed to implement two unique protocols used for the transfer of operational and configuration data as required by the wireless modems. Whether data is being sent or received or configuration commands are being issued to the modem, the Proxim packet exchange protocol (PPX-1 Layer 2 Protocol) is used for all communication between the modem and the wireless sensing unit's core. A packet is a list of bytes that encode information understandable by the wireless modem. Within the packet exchange protocol, a modem command protocol (MCP) is encoded that specifies a command to the modem such as transmit data or modify specific configuration settings.

The fourth module is responsible for controlling the A/D converter of the wireless sensing unit. Various functions are implemented in the module that can initialize the converter, set the converter to a desired sampling rate, as well as provide a means to read the converter's digital data and to store the data in memory.

4. Application software - embedded engineering analyses

The application software layer of the wireless sensing unit is written in a modular fashion, similar to that of the device drivers. Different modules can be embedded that are intended for a variety of applications ranging from modal analysis to structural health monitoring. A large body of literature exists focusing on the detection of damage in structures. Various methods have been proposed that examine measured structural responses in both the time and frequency domains. For example, a large number of the proposed methods depend on changes in the modal properties of a structure to identify the existence of damage. As a result of the environmental and operational variability of civil structures, damage detection methods based on modal properties have been successful only when significant damage is present (Doebling *et al.* 1996). More recently, Sohn and Farrar (2001) have proposed using time-series analysis for the identification of damage in civil structures. The time-series approach has shown great promise in the identification of damage, particularly for structures subjected to significant operational variability. The method has been successfully employed for the identification of damage in different structures including the hull of a high-speed patrol boat, laboratory test specimens, and a large-scale benchmark structure design and tested by the ASCE Task Group on Health Monitoring (Sohn *et al.* 2001, Sohn and Farrar 2001, and Lei *et al.* 2003a).

This study primarily focuses on two application modules to present the full capabilities of the unit's computational core. The first performs the computationally efficient fast Fourier transform (FFT) to derive the frequency response function (FRF) of a structural system from measured response time-histories. Continuous identification of the system's modes of response is important for tracking significant changes that are correlated to structural damage. The second application module implements auto-regressive modeling of time-history data. Auto-regressive (AR) models possess features sensitive to damage in a structural system. Realistic data interrogation algorithms, taken from damage detection methods, are to illustrate the potential of the wireless sensing unit for use in future automated structural health monitoring systems.

4.1 Implementation of the fast Fourier transform

The FRF of a structural system can be calculated directly from measurement data by using the computationally efficient fast Fourier transform (FFT). The discretely measured response of a system in the time domain, h_k, is converted to the response in the frequency domain, H_n, by means of a discrete Fourier transform, as presented in Eq. (1).

$$H_n = \sum_{k=0}^{N-1} h_k e^{2\pi ikn/N} \tag{1}$$

where N represents the total number of time-history samples.

If the discrete Fourier transform of Eq. (1) is directly calculated by the wireless sensing unit, the calculation is an $O(N^2)$ process. Utilization of the discrete fast Fourier transform can reduce this calculation to an $O(N\log_2 N)$ process representing a significant increase in computational efficiency. Various forms of the FFT are available for use, but the Cooley-Tukey method is used in this implementation (Press *et al.* 1992). The Cooley-Tukey method begins with a reordering of the original time-history data and reduces to two-point Fourier transforms between adjacent time samples.

4.2 Statistical pattern recognition paradigm for damage detection

Sohn and Farrar (2001) proposed using time-series analysis for the identification of damage in civil structures. It is part of a damage detection framework which consists of four-parts: evaluation of a structure's operational environment, acquisition of structural response measurements, extraction of damage sensitive features and use of statistical models for feature discrimination (Sohn *et al.* 2001).

The time-history analysis begins with measurement of the structural response of the undamaged structure at a particular sensor location. Assuming the response to be stationary, an auto-regressive process model, also known as an infinite impulse response (IIR) filter, is used to fit the discrete measurement data sampled at a period of Δt:

$$x_k = \sum_{i=1}^{p} b_i^x x_{k-i} + r_k^x \tag{2}$$

The response of the structure at time $t = k\Delta t$, denoted by x_k, is a function of p previous observations of the response of the system, plus, a residual error term, r_k^x. Weights on the previous observations of x_{k-i} are denoted by the b_i coefficients.

The residual error of the AR model is a damage sensitive feature, but it is also influenced by the operational variability of the structure. To separate changes in the residual error resulting from structural damage and operational variability, an auto-regressive with exogenous input (ARX) time-series model is used to model the relationship between the AR model residual error, r_k^x, and the measured response, x_k:

$$x_k = \sum_{i=1}^{a} \alpha_i x_{k-i} + \sum_{j=0}^{b} \beta_j r_{k-j}^x + \varepsilon_k^x \tag{3}$$

Coefficients on past measurements and the residual error of the AR model are α_i and β_j, respectively. The residual of the ARX model, ε_k^x, is the damage sensitive feature used to identify the existence of damage regardless of the structure's operational state. Determination of the AR and ARX model orders (p, a, and b) are done by exploring the autocorrelation function of the model residual errors. The model orders selected correspond to the autocorrelation lag where the autocorrelation function is nearly zero (Sohn *et al.* 2001).

To implement the statistical pattern recognition approach, the structure is observed in its undamaged state under a variety of environmental and operational states to populate a database pairing AR(p) models of dimension p and ARX(a, b) models of dimension a and b. Next, the response of the structure, y_k, in an unknown state (damage or undamaged) is measured and an AR(p) model is fit. The coefficients of the fitted AR model are compared to the database of AR-ARX model pairs previously calculated for the undamaged structure. A match is determined by minimizing the sum of the difference of the newly derived AR model and the database AR models coefficients, b_i^y and b_i^x respectively. If no structural damage is experienced and the operational conditions of the two models are close to one another, the selected database AR model should closely approximate the measured response. If damage has been sustained by the structure, even the closest AR model of the database will not approximate the measured structural response well.

The measured response of the structure in the unknown state, y_k, and the residual error of the fitted AR model, r_k^y, are substituted in the database ARX model of Eq. (3) to determine the residual error, ε_k^y, of the ARX model:

$$y_k = \sum_{i=1}^{a} \alpha_i y_{k-i} + \sum_{j=0}^{b} \beta_j r_{k-j}^y + \varepsilon_k^y \tag{4}$$

Since the residual of the ARX(a, b) model is the damage sensitive feature in the analysis, if the structure is in a state of damage, the statistics of the ARX model residual, ε_k^y, will vary from that of the ARX model corresponding to the undamaged structure. It has been shown that damage can be identified when the ratio of the standard deviation, σ, of the model residuals exceeds a threshold value established from good engineering judgment as shown in Eq. (5) (Sohn *et al.* 2001).

$$\frac{\sigma(\varepsilon_k^y)}{\sigma(\varepsilon_k^x)} \geq h \tag{5}$$

Establishing a threshold, h, that minimizes the number of false-positive and false-negative identifications of damage is necessary for robust damage detection.

4.2.1 Implementation of auto-regressive time series modeling

A software module is written for the units' embedded application layer that determines the coefficients of an AR(p) model based on a segment of the recorded data. Multiplying both sides of Eq. (2) by the current measurement sample, x_k, and taking the expected value of both sides, the autocorrelation function, $\varphi(k)$, of the auto-regressive process is derived:

$$\varphi_{xx}(k) = \sum_{i=1}^{p} b_i^x \varphi_{zz}(k-i) \tag{6}$$

The autocorrelation function of the discrete time history obeys the initial difference equation of the AR process. This yields a means of determining the coefficients of the AR process based on calculations of the autocorrelation of the measurement data. Resulting are the Yule-Walker equations (Gelb 1974):

$$\begin{bmatrix} \varphi_{xx}(0) & \varphi_{xx}(1) & \dots & \varphi_{xx}(p-1) \\ \varphi_{xx}(1) & \varphi_{xx}(0) & \dots & \varphi_{xx}(p-2) \\ \vdots & \vdots & \ddots & \vdots \\ \varphi_{xx}(p-1) & \varphi_{xx}(p-2) & \dots & \varphi_{xx}(0) \end{bmatrix} \begin{Bmatrix} b_1 \\ b_2 \\ \vdots \\ b_p \end{Bmatrix} = \begin{Bmatrix} \varphi_{xx}(1) \\ \varphi_{xx}(2) \\ \vdots \\ \varphi_{xx}(p) \end{Bmatrix} \tag{7}$$

The autocorrelation values of Eq. (7) can simply be estimated from the measurement data consisting on N samples by:

$$\varphi_{xx}(k) \cong \frac{1}{N-k} \sum_{i=1}^{N-k} x_i x_{i+k} \tag{8}$$

Coefficients of the auto-regressive process are extremely sensitive to the way the autocorrelation of the process is determined. Burg's method has been proposed by Press *et al.* (1992) for determining the coefficients of the auto-regressive model directly from the measurement data. The method is recursive with its order increasing during each recursive call by estimating a new coefficient b_i and re-estimating the previously calculated coefficients so as to minimize the residual error of the process. Alternatively, a least-square approach can be taken to determine the coefficients of the auto-regressive model. While using least-squares is less computationally intensive, Burg's approach is more accurate. Furthermore, Burg's method exhibits better solution stability because matrix inversion is not a necessary step in the solution.

5. System validation

To validate the performance of the wireless sensing unit, validation tests upon a laboratory test structure are devised. A five-story shear frame structure, made from aluminum, is employed as shown in Fig. 3. The lateral stiffness of each floor originates from the four vertical aluminum columns roughly 1.27 cm by 0.64 cm in cross sectional area. The mass of each floor is approximately 7.25 kg. From log-decrement calculations of free vibration tests, the damping of the structure is approximated to be 0.5% of critical damping. A theoretical lumped-mass shear structure is modeled using the mass, stiffness and damping properties of the real structure. This theoretical model will serve as a comparison system for the experimental results.

The entire structure is fastened to the top of a one-directional lateral shaking table driven horizontally by a 49 kN actuator. Various excitations are applied at the base of the structure to dynamically excite the system. To monitor the response of the structural system to the different input excitations, a wireless sensing unit is securely fastened to the fourth story of the structure. At the top of the structure, a low-cost micro-electro mechanical system (MEMS) accelerometer is

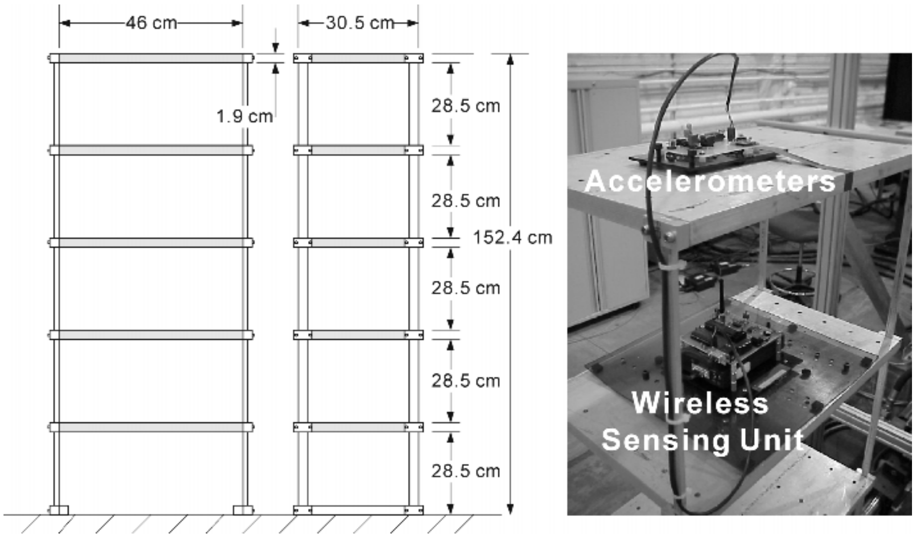

Fig. 3 Test structure for laboratory validation of the prototype wireless sensing unit

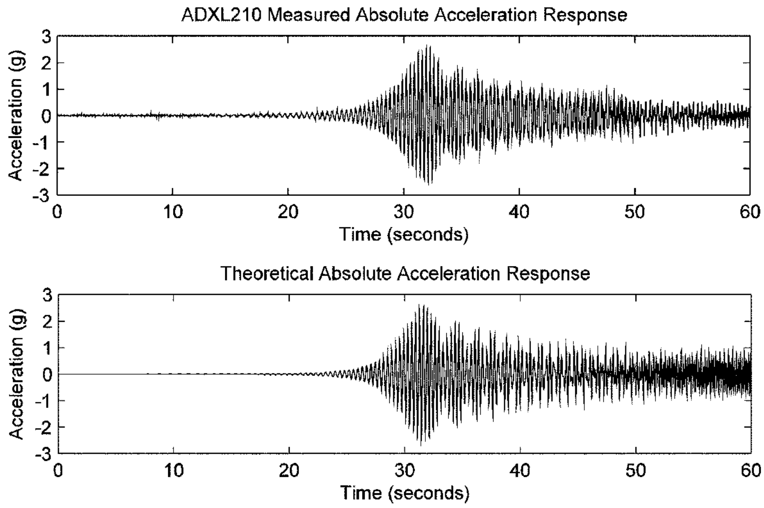

Fig. 4 Actual measured (top) and theoretical (bottom) absolute acceleration response of the test structure

mounted for measurement of the structure's absolute acceleration response. In particular, the Analog Devices ADXL210 accelerometer, capable of measuring +/−10 g acceleration, is selected. For this set of experiments, the bandwidth and noise floor of the accelerometer are set to 50 Hz and 4.33 mg, respectively.

5.1 Calculation of the structural frequency response function

A swept-frequency sine, also known as a chirping excitation, is applied to the base of the structure

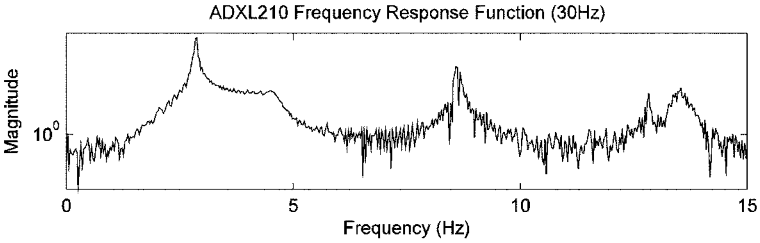

Fig. 5 Frequency response function derived from the structural acceleration response

in order to excite its lower modes of response. The chirping excitation has constant displacement amplitude of 0.2 cm with a linearly varying frequency of 0.25 to 3 Hz over 60 seconds. During the excitation, the acceleration response of the fifth story is monitored. The measurement data is sampled at 30 Hz, well above the primary modes of response of the system analytically determined to be 2.96, 8.71, 13.70, 17.47, and 20.04 Hz. Fig. 4 presents the absolute acceleration response of the shear structure to the input motion generated by the shaking table. The absolute acceleration response measured using the accelerometer is in very good agreement with the analytically determined theoretical response.

The frequency response function of the recorded time-history is locally calculated from an embedded FFT algorithm. The FFT is performed on 1024 consecutive time points of the response between 10 and 44 seconds. The first three modes of response of the structure can be visually identified from the calculated response function as shown in Fig. 5. The modes are determined to be 2.87, 8.59, and 13.54 Hz. The frequencies of the calculated modes are within 3% of those calculated from the theoretical model.

5.2 Auto-regressive time-series modeling

A stationary response of the structural system is required for fitting AR models. Assuming the system to respond linearly, a stationary white noise input to the structure is used to derive a stationary white-noise response at the structure's top story. The test structure is excited by a white noise excitation with zero mean and a 0.13 cm standard deviation. The absolute acceleration response of the structure, as measured by the ADXL210 accelerometer is shown in Fig. 6. The time-history acceleration response of the structure as measured in this manner is relatively stationary with zero mean and a standard deviation of approximately 1.1 g. Therefore, the record is suitable to

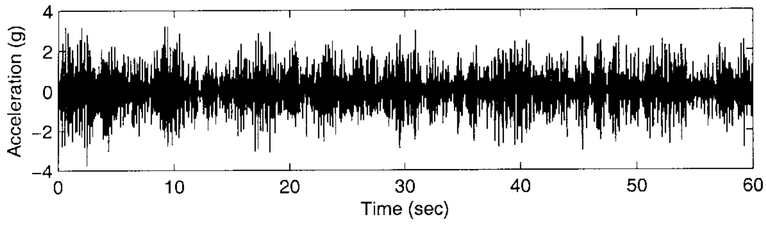

Fig. 6 Absolute acceleration response of fifth-story to a white noise input excitation

Table 1 Coefficients of a fitted auto-regressive model to stationary structural response

Coefficient, b_i	AR_{10}	
	PowerPC	MATLAB
b_1	1.6650	1.6650
b_2	1.3009	1.3009
b_3	0.4752	0.4752
b_4	0.1171	0.1171
b_5	0.6756	0.6756
b_6	1.5212	1.5212
b_7	1.2646	1.2646
b_8	0.5989	0.5989
b_9	0.1498	0.1498
b_{10}	0.0891	0.0891

fitting an auto-regressive time-series model.

After recording the acceleration response of the test structure, an auto-regressive model of 10 coefficients is fit to the measurement data of Fig. 6. After logging the coefficients, an identical analysis is performed using Burg's auto-regressive function provided by MATLAB to compare the accuracy of the coefficients determined by the wireless sensing unit. The coefficients determined by the wireless sensing unit and MATLAB, as presented in Table 1, are identical as expected.

6. Conclusions

This paper describes the design of a wireless sensing unit for potential application in an autonomous structural health monitoring system. The wireless sensing unit has been tested on the Alamosa Canyon Bridge, New Mexico, for performance comparison to a cable-based monitoring system (Lynch 2002). As a low-cost alternative to commercial tethered monitoring systems, the units have the distinct advantage of integrated computational power for embedded engineering analyses. This study focuses on the potential for embedment of damage detection algorithms in the sensing units for local data processing. The computational core of the proposed wireless sensing unit is designed to accommodate a broad set of engineering analyses. For this study, FFT and AR modeling capabilities were embedded. The FFT is a widely used tool for structural system identification as well in some damage detection methods. Determination of AR models from stationary structural responses represents the first step towards a full implementation of the statistical pattern recognition paradigm for detection of structural damage. The time-series based damage detection analyses have been shown effective in the identification of damage in structures with substantial operational variability (Sohn *et al.* 2001).

For validation of the wireless sensing unit's hardware and software performance, a MEMS-based accelerometer is interfaced to the wireless sensing unit. Both the accelerometer and unit are installed in a simple laboratory structure for measurement of the structure's top story absolute acceleration response. First, the embedded FFT method is performed to derive the FRF of the system when excited by a sweep sinusoid signal. A clean FRF resulted with the first three modes of the structure easily identifiable. In a second validation test, the structure is excited by a stationary white noise input with a 10 coefficient AR model fit to the acceleration response. The coefficients obtained were identical to those calculated using MATLAB. In summary, the engineering analyses chosen for integration in the wireless sensing unit's computational core performed as design.

Additional research is warranted to improve both the hardware and software designs of the current wireless sensing unit prototype. With respect to engineering analyses, a large number of algorithms exist that could be embedded in the wireless sensing unit. This study has illustrated the ability of the wireless sensing units to locally execute embedded engineering analyses. A large number of algorithms that are used for digital filtering, system identification and damage detection can be embedded in the units. Future research is required to validate the ability of the proposed wireless sensing units to autonomously detect damage from structural response measurements obtained from laboratory and full-scale field structures. Additional exploration is required to assess which damage detection methods are best suited for embedment in the computational core of the wireless sensing unit. For example, careful attention should be paid to avoid those approaches that are computationally exhaustive or require user intervention for tuning. Nevertheless, algorithms that can be embedded with sensing hardware will be beneficial in reducing the demand on both computations in a central unit and the amount of data communicated in a wireless environment.

For system identification applications, the wireless sensing unit design should include a means for synchronizing the network of sensors to a common clock. The current prototype presented in this paper has not been design for synchronization with other units. Straser and Kiremidjian have been able to illustrate the ability to synchronize wireless sensing units to within 0.1 milliseconds using a frequency modulated (FM) beacon signal. Research has begun to explore *a posteriori* techniques for synchronizing time-history records using time-series predictive modeling approaches (Lei *et al.* 2003b).

Acknowledgements

This research is partially sponsored by the National Science Foundation under Grant Numbers CMS-9988909 and CMS-0121842. The fruitful suggestions provided by Dr. Chuck Farrar and Dr. Hoon Sohn of Los Alamos National Labs have been invaluable to the progress of our research.

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