

EMBEDDING ALGORITHMS IN A WIRELESS STRUCTURAL MONITORING SYSTEM

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ABSTRACT

A complex wireless sensing unit is designed for application in structural monitoring systems. Fabricated from advanced embedded system technologies, the prototype unit employs a spread-spectrum wireless modem for peer-to-peer communication between sensing units and a complex 32-bit computational core for local data interrogation. Utilizing the computational capabilities of the sensing unit design, a collection of structural health monitoring software applications can be implemented for execution by the units. Fast Fourier transforms and methods for fitting auto-regressive time-series models are employed as illustrative algorithms embedded in the wireless sensing unit. The research goal is a wireless sensing network supporting the collaborative processing of real-time measurement data for the identification of potential damage in a structural system.

INTRODUCTION

The field of structural engineering has historically derived tremendous benefit from the installation of structural monitoring systems. Data generated by structural monitoring systems provide insight to the performance of a structure over its operational life and during large external disturbances such as earthquakes. The current state-of-technology is characterized by centralized systems that employ sensors (such as accelerometers) wired to a centralized data acquisition system. The use of wires as the sole medium for data transfer from system sensors to data servers cause systems to have high installation and maintenance costs. As a result, the adoption of the technology is defined as sluggish. With installation and maintenance costs high for tethered systems, Straser (1998) proposed employing wireless communication technology to serve as a cost effective and reliable alternative for current cabled structural monitoring systems.

The past decade has witnessed the explosive growth of wireless communications along with major advancements of integrated circuit and embedded system technologies. For wireless communication and embedded system technologies, the cost of hardware components continues to decrease while their functional capabilities broaden. As a result, a wireless sensing unit is designed and constructed from off-the-shelf hardware components to serve as the fundamental building block of wireless modular

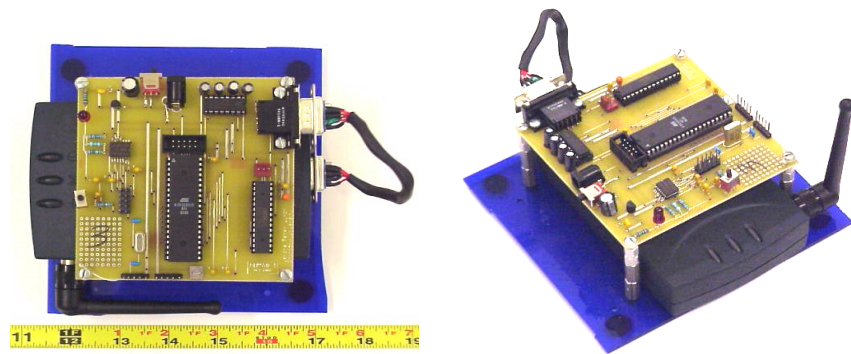


Figure 1 – Prototype wireless sensing unit

monitoring systems (WiMMS). Key features of the unit include wireless communications, high resolution 16-bit digital conversion of interfaced sensors, and a powerful computational core that can perform various data interrogation techniques in near real-time (Lynch et al. 2002). The computational core's architecture is designed using two processors. The first is a low-power 8-bit Atmel microcontroller included for data acquisition functions such as reading measurements from interfaced sensors. The second, a 32-bit Motorola PowerPC microcontroller that supports hardware floating point calculations, is included in the design to perform the data interrogation tasks. The unit is compact at 20 in.³ and the current total component cost is less than \$500. A picture of the prototype wireless sensing unit is shown in Figure 1.

With a flexible and capable hardware design, the wireless sensing units are to be implemented with the computational tasks required by a structural health monitoring system. Structural health monitoring algorithms can be embedded in the wireless sensing unit to assess changes in the system, and if appropriate, infer potential structural damage from time-history measurement data. To validate the sensing unit's role as a computational agent for structural health monitoring applications, two algorithms are embedded to locally process measurement data. The first is the fast Fourier transform that will be used to derive the frequency response function from time-history data; the frequency response function serves as the basis for many frequency-domain damage detection approaches. The second algorithm, representing the first step in a novel time-domain damage detection method, is the fitting of an auto-regressive time series model to time-history data. The functionality of both computational methods is to be illustrated on response measurements obtained from a laboratory test structure excited by a shaking table.

OVERVIEW OF STRUCTURAL HEALTH MONITORING ALGORITHMS

Structural health monitoring (SHM) is defined as the computational paradigm used to quantify a structure's health and well-being over its operational life. Application of SHM concepts to a diverse set of structures, ranging from aircrafts to traditional civil structures, has tremendous benefit in assessing safety and remaining operational life. While still in its infancy, researchers in the SHM field have produced a variety of algorithms for the identification of damage in structures. To date, methods developed for damage detection can be classified as frequency-domain or time-domain approaches.

The earliest damage detection methods correlated damage to changes in structural stiffness. The methods use finite element models and linear modal parameters, such as natural frequencies and mode shapes, to identify the existence of damage and in some cases, even damage location and severity

(Doebbling et al 1996). Modal properties, like natural frequencies of a structure's modes, are observed in the healthy structure. If major changes are observed in modal properties over a structure's operational life, the changes could be attributed to damage. The extraction of modal parameters from frequency response functions derived from vibration-based test data follows closely the developments in traditional modal testing (Ewins 1984). Classified as frequency-domain approaches, these methods had success in identifying large levels of damage in a structure but suffered from an inability to positively identify the onset of damage (Sohn and Farrar 2001). With respect to civil structures, environmental and operational variability can also cause changes in natural frequencies and mode shapes, rendering frequency-domain approaches difficult to apply except in cases of extreme damage (Sohn et al. 1999).

In response to the difficulties associated with applying frequency-domain techniques to civil structures, new approaches to damage detection are being explored. In particular, approaches based upon the statistical pattern recognition paradigm appear promising (Sohn et al. 2001). This time-domain approach entails the use of statistical signal processing techniques applied on time-history measurement data to infer the existence of damage in the structural system. The approach extensively uses linear predictive time-series models. Assuming the structural response to be stationary, an auto-regressive (AR) time-series model can be fit to time-history measurement data:

$$x_k^x = \sum_{i=1}^p b_i^x x_{k-i}^x + r_k^x \quad (1)$$

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 coefficient, b_i . The residual error of the AR model is a damage sensitive parameter, but it is also influenced by the operational variability of the structure. To separate changes in the residual error resulting from 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 :

$$x_k = \sum_{i=1}^a \alpha_i x_{k-i} + \sum_{j=0}^b \beta_j r_{k-j}^x + \varepsilon_k^x \quad (2)$$

The residual error 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. To implement the statistical pattern recognition approach, a 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 .

After measuring the response of a structure, denoted by y_k , in an unknown state (damaged or undamaged), 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 made by minimizing the difference (in a Euclidean sense) between the coefficients of the AR model calculated and an AR model from the database. If no structural damage is experienced and the operational conditions of the two models are close to one another, the selected AR database 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.

With an AR-ARX model pair selected from the database, the measured response, y_k , and residual error, r_k^y , of the fitted AR model are substituted in the ARX model of Equation (2) to determine the

residual error, ε_k^y . 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, ε_k^x , corresponding to the undamaged structure. The damage can then be identified when the ratio of the standard deviation of the model residuals exceeds a threshold value established from good engineering judgment:

$$\frac{\sigma(\varepsilon_k^y)}{\sigma(\varepsilon_k^x)} \geq h \quad (3)$$

Application of the linear prediction time-series model has been illustrated for a variety of structures from fast patrol boats to lumped mass models (Sohn and Farrar 2001, Sohn et al. 2001).

EMBEDDED SOFTWARE DESIGN

To illustrate the units' utility in an automated structural health monitoring system, two computational algorithms are selected and encoded for embedment in the prototype wireless sensing units. The first algorithm is the fast Fourier transform (FFT) used to derive the frequency response function (FRF) from time-history data collected by the units. The second computational algorithm to be embedded is an auto-regressive (AR) time series fitting algorithm.

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:

$$H_n = \sum_{k=0}^{N-1} h_k e^{2\pi i k n / N} \quad (4)$$

where N represents the total number of time-history samples. If the discrete Fourier transform of Equation (4) is directly calculated by the wireless sensing unit, the calculation is an $O(N^2)$ process. Utilization of the discrete fast Fourier transform reduces this calculation to an $O(N \log_2 N)$ process. Although various forms of the fast Fourier transform are available for use, our implementation of the algorithm for embedment in the sensing unit's core follows closely the Cooley-Tukey method (Press et al. 1992). The approach reorders the initial time-history data and performs a series of two-point Fourier transforms on adjacent data points.

Auto-Regressive Time Series Modeling

The wireless sensing units can individually perform most of the computations associated with the statistical pattern recognition algorithms. The role of the unit is well defined with the responsibility of recording the structural response, normalizing the response, and fitting AR models to the measurements. After the AR model is fit, the model's coefficients would be wirelessly communicated to a centralized data server housing a database populated by AR-ARX model pairs. Once a model match is made, the coefficients of the ARX model are transmitted to the wireless sensing unit where the standard deviation of the ARX model is calculated. The ratio of standard deviations of ARX model errors shown in Equation (3) is calculated and compared to a previously established threshold.

Software is written for the wireless sensing unit to determine the coefficients of an AR(p) model based on a segment of the recorded data. Multiplying both sides of Equation (1) by the current measurement sample, x_k , and taking the expected value of both sides, the autocorrelation function of the auto-regressive process is derived:

$$\varphi_{xx}(k) = \sum_{i=1}^p b_i^x \varphi_{zz}(k-i) \quad (5)$$

where $\varphi_{xx}(k)$ are the discrete terms of the autocorrelation function of x_k . The autocorrelation function 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):

$$\begin{bmatrix} \varphi_{xx}(0) & \varphi_{xx}(1) & \cdots & \varphi_{xx}(p-1) \\ \varphi_{xx}(1) & \varphi_{xx}(0) & \cdots & \varphi_{xx}(p-2) \\ \vdots & \vdots & \ddots & \vdots \\ \varphi_{xx}(p-1) & \varphi_{xx}(p-2) & \cdots & \varphi_{xx}(0) \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_p \end{bmatrix} = \begin{bmatrix} \varphi_{xx}(1) \\ \varphi_{xx}(2) \\ \vdots \\ \varphi_{xx}(p) \end{bmatrix} \quad (6)$$

Coefficients of the auto-regressive process are very sensitive to the way the autocorrelation of the process is determined. As a result, 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.

SOFTWARE VALIDATION

To validate the performance of the wireless sensing unit in a structural health monitoring setting, validation tests upon a laboratory test structure are devised. A five-story shear frame structure, made from aluminum, is employed as shown in Figure 2. The lateral stiffness of each floor originates from the four vertical aluminum columns roughly 0.5 inches by 0.25 inches in cross sectional area. Each floor weighs 16 pounds. From log-decrement calculations of free vibration tests, the damping of the structure is approximated to be 0.5% of critical damping. The wireless sensing unit is securely fastened to the fourth story while the Analog Devices ADXL210 MEMS-based accelerometer is mounted upon the fifth story. The entire structure is fastened to the top of a one-directional lateral shaking table driven horizontally by an 11 kip actuator. Various excitations are applied at the base of the structure to dynamically excite the system.

Determination of the Frequency Response Function

A swept-frequency sine, also known as a chirping excitation, is applied to the base of the structure in order to excite the lower modes of response of the system. The chirping excitation has constant displacement amplitude of 0.075 inches 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.

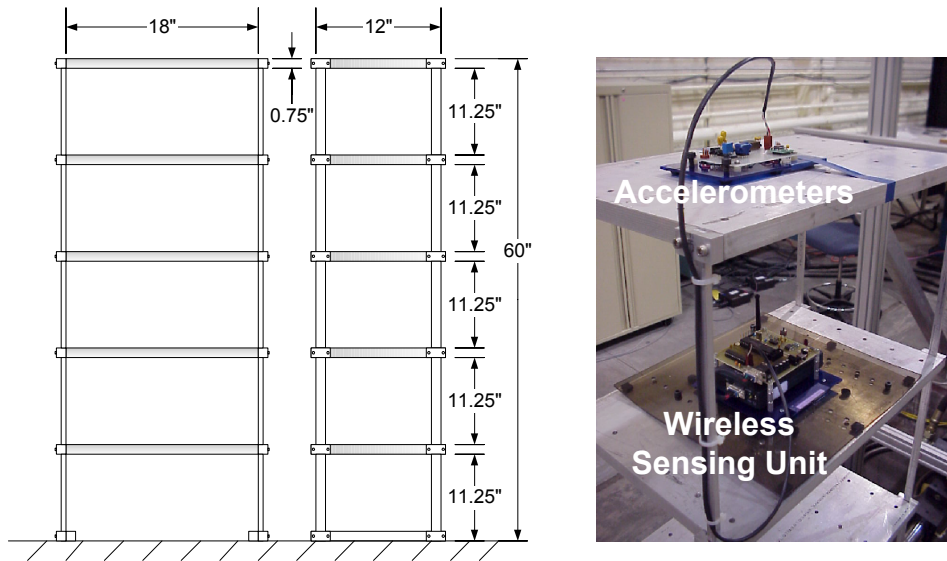


Figure 2 – Five-story lumped-mass shear structure mounted upon a shaking table

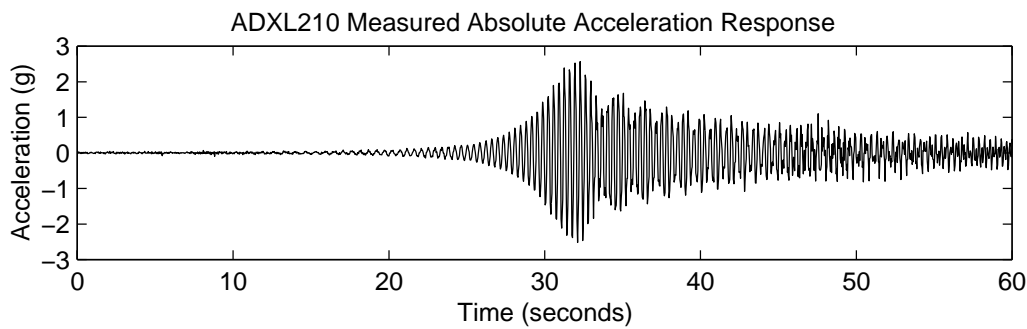


Figure 3 - Absolute acceleration response at the fifth story from a sweep input excitation

Figure 3 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 theoretical response determined analytically.

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 functions as shown in Figure 4. 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.

Auto-Regressive Time Series Model Fitting

The test structure is excited by a white noise excitation (zero mean and 0.05 inch standard deviation) and the accelerometer on the fifth story measures the acceleration response as shown in Figure 5.

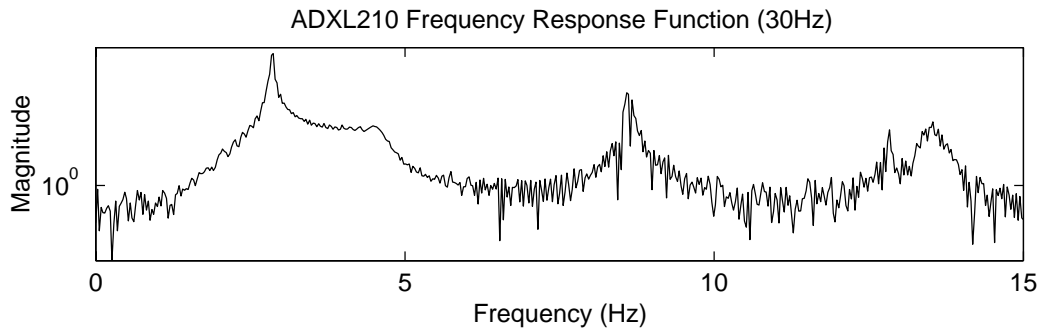


Figure 4 - Frequency response function derived from the structural acceleration response

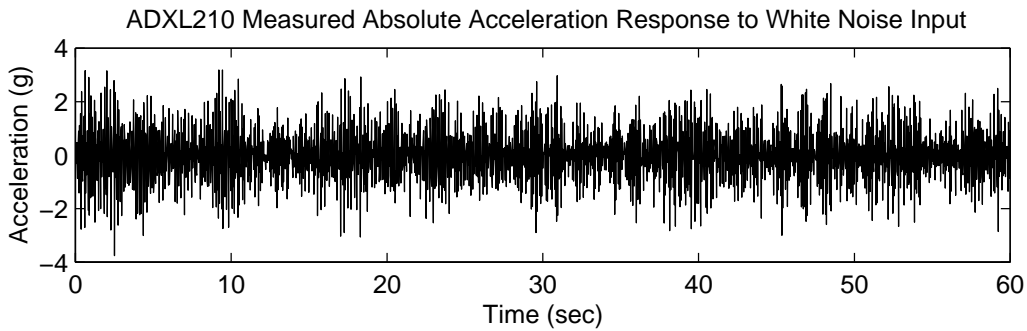


Figure 5 – Absolute acceleration response of fifth-story to a white noise input excitation

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 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 Figure 5. 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.

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

CONCLUSION

The realization of an automated structural health monitoring system has taken one step forward with the development of a wireless sensing unit constructed with advanced embedded system technologies. The result is a hardware design that is optimized for tasks specific to structural health monitoring applications. In particular, an advanced computational core is provided that is capable of locally processing measurement data to assess the state and possibly identify damage in a structure. A fast Fourier transform algorithm and an auto-regressive time series algorithm have been embedded in the unit to illustrate the unit's computational capabilities. Both applications have been successfully applied to time-history measurement data taken from a five degree-of-freedom laboratory structure excited by a shaking table.

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