Source: *Proceedings of Advances in Structural Engineering and Mechanics (ASEM'02)*, Pusan, Korea, August 21-23, 2002.

Computational Core Design of a Wireless Structural Health Monitoring System

Jerome P. Lynch[1], Arvind Sundararajan[2], Kincho H. Law[3], Anne S. Kiremidjian[3], Thomas Kenny[4], and Ed Carryer[4]

The John A. Blume Earthquake Engineering Center, Stanford University, Stanford, CA 94305

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 to the network. To perform the computationally intensive task of damage detection, an advanced PowerPC computational core is chosen. First, a layer of software comprised of various device driver modules is developed to operate the various hardware subsystems of the wireless sensing unit. Additional software is then designed for embedment that can locally execute a time-series based damage detection algorithm.

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). Other applications have included permanent installation in structures controlled by structural control systems as well as in temporary installation for identification of modal properties. Current monitoring systems are characterized by hub-spoke architecture with

[1] PhD Candidate, correspondence can be sent to: jplynch@stanford.edu
[2] Research Assistant
[3] Professor of Civil and Environmental Engineering
[4] Professor of Mechanical Engineering

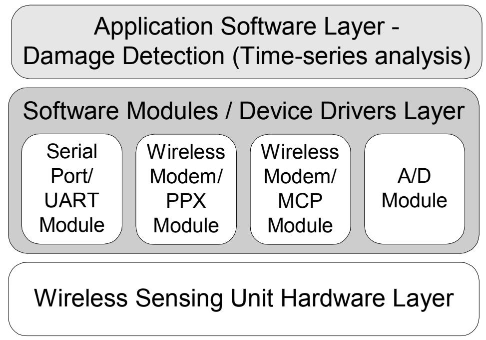

Figure 1. Hardware, device-driver modules, and application software layers

sensors connected directly to a centralized data server via wires. The cost of wired-based monitoring systems is high due to the high cost associated with the installation and maintenance of the wires.

Using available technologies from the marketplace, a low-cost wireless monitoring system is presented as an alternative to the expensive wire-based systems. Coupled with each sensor will be a means of wireless communications for the relay of real-time measurement data to a network of sensor nodes. Furthermore, computational power will be coupled with each wireless sensing unit to allow for the local processing of measurement data. Through the coupling of these two technological innovations, a low-cost yet tremendously powerful wireless modular monitoring system (WiMMS) can be delivered. The computational core of the wireless sensing units will facilitate parallel data processing, rendering automated damage detection procedures feasible in real-time. The data communication architecture of the system is no longer confined to the traditional centralized style, with wireless peer-to-peer (P2P) communication between sensing units now attainable.

The hardware design of the wireless sensing unit will be briefly discussed with the design of embedded software presented in detail. The software design can be divided into two layers: the device driver layer and the application layer as shown in Figure 1. Device driver modules are written to independently operate the various hardware subsystems of the wireless sensing unit. An application layer is presented that implements an automated damage detection method using time-series analysis. With wireless sensing units acting as local damage detectors, a WiMMS system intended for structural health monitoring is realized.

WIRELESS SENSING UNIT PROTOTYPE DESIGN

The hardware design of the wireless sensing unit proposed by Lynch et al. (2001) can be divided into three broad categories: 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 easily be used. 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 sample rate of the A/D converter is variable and can be easily adjusted by the computational core.

The computational core's microcontroller is an important part of the sensing unit's design. Its role is to operate the entire sensing unit including the control of the A/D converter and the wireless modem. In addition, the computational core is responsible for the implementation of algorithms intended for damage detection, modal analysis and structural control. In particular, a 32-bit PowerPC microcontroller is selected to serve as the computational core. Supporting fast floating-point operations in hardware and having plenty of ROM and RAM memory, the Motorola MPC555 PowerPC serves as a suitable core choice balancing computational power with moderate power consumption characteristics.

Responsible for communications between each wireless sensing unit and the sensing network, Proxim RangeLAN2 wireless modems are chosen. Communicating in the 2.4 GHz, unlicensed FCC radio band, the RangeLAN2 modems can communicate at ranges as high as 1000 feet in open space. Depending on the building construction, this range can be reduced to distances as low as 500 feet 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 Figure 2. The size of the current prototype is about 16 cubic inches and components cost only a few hundred dollars. Further improvement on both the form factor and cost is possible.

THE HARDWARE-SOFTWARE INTERFACE

Software that is interfacing with hardware is the lowest layer of software abstraction. Its role is to operate and control the unit's hardware to assist upper software layers in accomplishing their computational goals. The functionality envisioned indicates 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. The modules, also known as device drivers, are typically written in a high level programming language such as C.

Four software modules are designed for control of the unit's hardware. The first module is 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

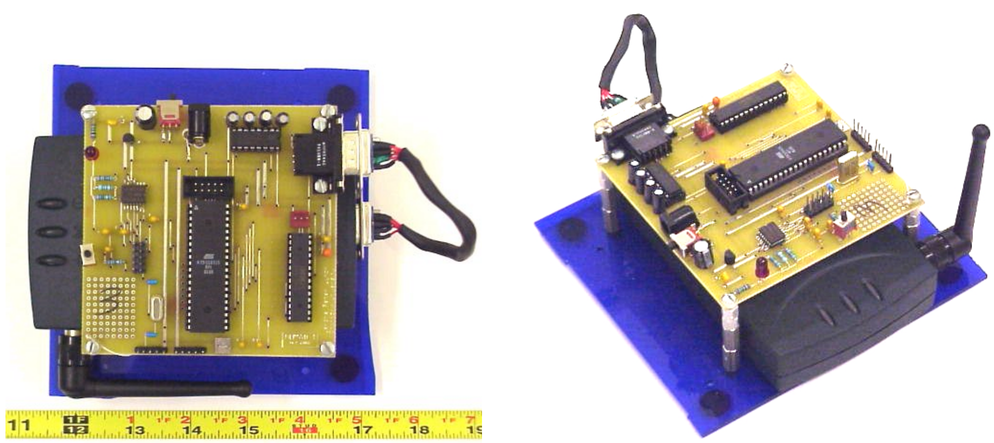

Figure 2. Completed wireless sensing unit prototype

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 implementing 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 specific configuration settings.

The forth module is responsible for the control of the wireless sensing unit's A/D converter. Various functions are specified in the module's implementation 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.

APPLICATION SOFTWARE LAYER

The application software layer of the wireless sensing unit is written in a modular fashion, similar to that of the device drivers. Various application modules can be written that are intended for applications ranging from modal analysis to structural control. This study will primarily focus on an application module written to automate the process of damage detection using a statistical pattern recognition paradigm.

Damage Diagnosis using the Pattern Recognition Paradigm

Structural health monitoring entails the use of damage detection algorithms for the identification of damage, as well as provides insight to location and severity. Particularly for civil structures, information on the integrity of a structure in near real-time can be instrumental in assessing its safety over its operational lifespan.

A rational approach to structural health monitoring is to develop a low-cost technology infrastructure for installation in a civil structure that can automate the process of detecting damage. The wireless sensing unit can serve as the fundamental building block of the automated system proposed. Using the computational power of the units, automated damage detection algorithms can be embedded that will interrogate the measurement data for the purpose of identifying and quantifying structural damage.

A large body of literature exists focusing on the detection of damage in a variety of structures. Various methods have been proposed examining the measurement response of a structure 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. Unfortunately, the environmental and operational variability of civil structures is a contributor to natural frequency and mode changes, rendering their change as the basis for damage identification difficult for civil structures except in cases where extreme damage is sustained (Sohn et al. 1999).

Statistical Pattern Recognition Paradigm – 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, the acquisition of structural response measurements, the extraction of measurement features that are sensitive to damage and the use of statistical models for feature discrimination (Sohn et al. 2001). The time series approach has shown great promise in the identification of damage in the hull of a high-speed patrol boat as well as in several laboratory test structures. In addition, the approach is a good candidate for embedment within the wireless sensing units.

The time history analysis begins with a measurement of the structural response at a particular sensor location. Assuming the response to be stationary, an autoregressive (AR) 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:

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

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 white noise error term, r_k^x. Weights on the previous observations of x_{k-i} are denoted by the b_i coefficients.

A database of AR(p) models of the same order, p, calculated from a wide assortment of time-history responses of the structure in a known structural state (undamaged) are collected. While the database is populated with models derived from one structural state, the models should be representative of the structure in a wide spectrum of operational conditions.

An AR(p) model is fit to a new measurement time-history, y_k, taken from a structure whose structural state (damage or undamaged) is unknown. This AR model is compared to each model of the structure's database to find a model that closely resembles it as determined by a minimum sum of the difference of the newly derived and the database 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 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. As a result, a second stage autoregressive model with exogenous inputs (ARX) is used to model the relationship between the database AR model's original time history measurement, $x(k\Delta t)$, and the model's residual error, r_k^x:

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

The residual of the ARX model is the last term of equation (2), ε_k^y. The measurement data corresponding to the unknown structural state is used in the same ARX(a,b) model obtained from the database:

$$y_k = \sum_{i=1}^{a} \alpha_i y_{k-i} + \sum_{j=0}^{b} \beta_j r_{k-j}^{\,y} + \varepsilon_k^{\,y} \tag{3}$$

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. In particular, it has been shown that damage can be identified when the ratio of the standard deviation of the model residuals exceeds a threshold value established from good engineering judgment (Sohn et. al. 2001):

$$\frac{\sigma\left(\varepsilon_k{}^y\right)}{\sigma\left(\varepsilon_k{}^x\right)} \geq h \tag{4}$$

Implementation of an Automated Damage Detection System - Using the prototype wireless sensing units, the time-series damage detection method is to be implemented. A centralized data server will be used in the system to store the database of AR(p) and ARX(a,b) models corresponding to various operational conditions of the undamaged structure. The centralized server is necessary since the memory associated with each sensing unit is not sufficient to hold the vast database.

With wireless sensing units installed throughout the system, the system response at various degrees-of-freedom is recorded. Prior to model fitting, the measurement data is normalized to have zero mean and a standard deviation of unity. 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 equation (1) by the current measurement sample, x_k, and taking the expected value of both sides, the autocorrelation function of the autoregressive process is derived:

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

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):

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

The autocorrelation values of equation (6) can simply be estimated from the measurement data consisting on N samples, by:

$$\varphi_{xx}(k) \cong \frac{1}{N-k} \sum_{i=1}^{N-k} x_i x_{i+k} \tag{7}$$

Coefficients of the autoregressive process are extremely sensitive to the way the autocorrelation of the process is determined. As a result, a method has been proposed by Press et al. (1992) for determining the coefficients of the autoregressive model directly from the

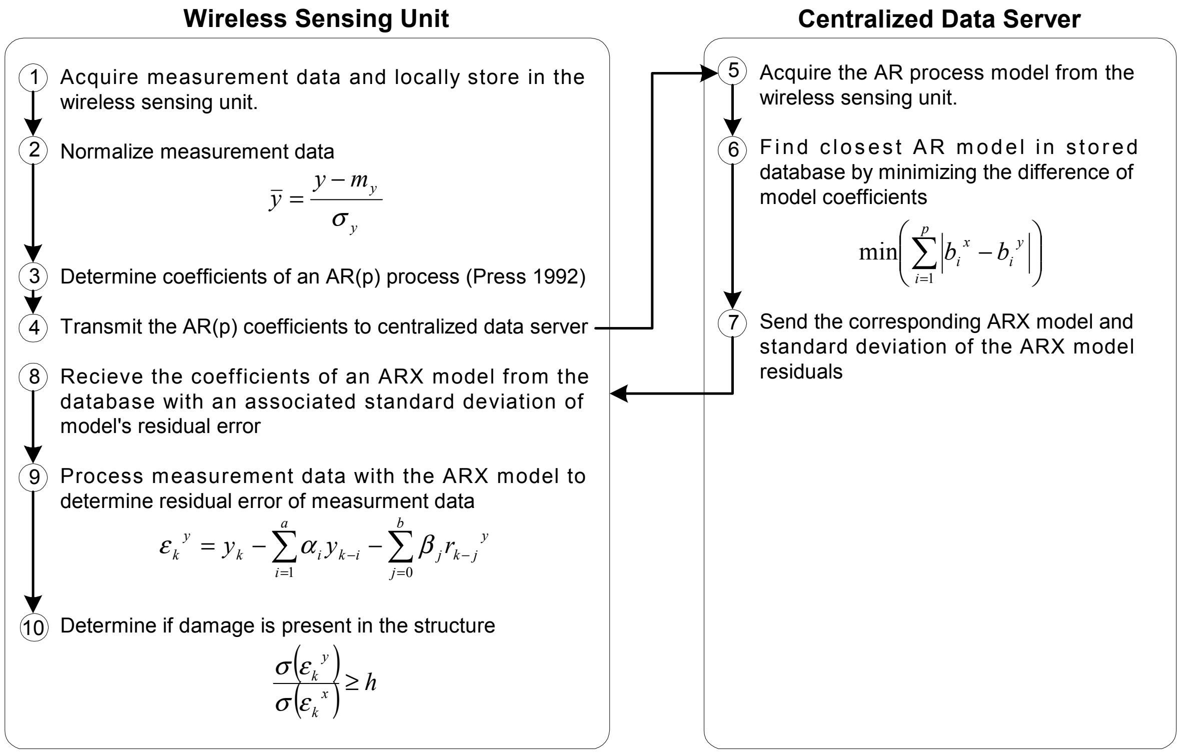

Figure 3. Implementation strategy of a time-series based structural health monitoring system

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.

<u>Application Strategy</u> - Once the autoregressive model has been locally determined by the wireless sensing unit using the measurement data, communication is established with the centralized data server. The p coefficients of the AR(p) process are sent to the centralized server for comparison to the database. Prior to the installation of the system, the number of autoregressive process coefficients is to be determined. The number can vary from 10 to 50 coefficients with the residual error of the autoregressive process decreasing with an increase in the number of coefficients. Determination of the closest AR model in the database is performed in the centralized server.

Once a match has been made, the coefficients of the ARX model corresponding to the AR model are returned to the sensing unit. The measurements stored in the wireless sensing unit are then used with the ARX model to determine the time history of the ARX residuals. The ratio of the standard deviation of the ARX residual corresponding to the measurement data, $\sigma(\varepsilon_k^{\,y})$, and that from the database, $\sigma(\varepsilon_k^{\,x})$, are compared to check if they exceed the damage threshold, h. The process is illustrated in Figure 3.

CONCLUSION

This study has focused upon the design of embedded software for the operation of the proposed wireless sensing units. Embedded software is necessary to harness the full potential provided by the state-of-art hardware selected for the unit's design. The software design is divided into two software layers: the lower layer operates the various hardware subsystems while the upper layer implements application algorithms. A modular software approach is employed to write device driver software resulting in four C modules. With respect to the application software layer, the use of a statistical pattern recognition paradigm for detection of damage is considered for implementation.

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.

REFERENCES

Gelb, A., (1974). *Applied optimal estimation*. M.I.T. Press, Cambridge, Massachusetts.

Hipley, P., (2001). "Caltran's current state-of-practice." *Proceedings of Instrumental Systems for Diagnostics of Seismic Response of Bridges and Dams*, COSMOS, Richmond, CA. 3-7.

Lynch, J. P., Law, K. H., Kiremidjian, A. S., Carryer, E., Kenny, T. W., Partridge, A., and Sundararajan, A., (2001). "Validation of a wireless modular monitoring system for structure." *Proceedings of 9th Annual International Symposium on Smart Structures and Materials*, SPIE, San Diego, CA.

Press, W. H., Teukolsky, S. A., Vetterling, W. T., Flannery, B. P., (1992). *Numerical recipes in C: the art of scientific computing*. 2nd ed. Cambridge University Press, Cambridge, U.K.

Sohn, H., Dzwonczyk, M., Straser, E. G., Kiremidjian, A. S., Law, K. H., and Meng, T., (1999). "An experimental study of temperature effect on modal parameters of the Alamosa Canyon Bridge." *Earthquake Eng. and Structural Dynamics,* John Wiley & Sons, **28**(9), 879-897.

Sohn, H., and Farrar, C. R., (2001). "Damage diagnosis using time series analysis of vibration signals." *Smart Materials and Structures*, Institute of Physics, **10**(2001), 446-451.

Sohn, H., Farrar, C. R., Hunter, N., and Worden, K., (2001). "Applying the LANL statistical pattern recognition paradigm for structural health monitoring to data from a surface-effect fast patrol boat." *Los Alamos National Laboratory Report No. LA-13761-MS*, University of California, Los Alamos, NM.