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Design of Wireless Sensor Units with Embedded Statistical Time-Series Damage Detection Algorithms for Structural Health Monitoring

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ABSTRACT

A low-cost wireless sensing unit is designed and fabricated for deployment in a structural monitoring system that uses wireless radios as the sole channel for communications. The finite operational life of portable power supplies such as batteries necessitates optimization of the wireless sensing unit design to attain power efficiency. To attain far reaching communication ranges required in structural monitoring applications, the wireless communication channel consumes significant amount of power. To reduce the quantity of raw time-history data for transmission and reception, a computational core that can accommodate localized processing of data is designed and implemented. To illustrate the ability of the computational core to execute embedded engineering analyses, a two-tiered time-series damage detection algorithm is implemented. Local execution of the embedded damage detection method is shown to save energy by avoiding utilization of the wireless channel to transmit raw time-history data.

INTRODUCTION

Many benefits can be gained from monitoring the ambient and forced response of civil infrastructures such as buildings, bridges, and dams. For example, determination of a structure's dynamic properties from ambient recorded responses can help engineers to identify structural vulnerabilities to large external disturbances. Recorded response data obtained by structural monitoring systems during earthquakes have been helpful in identifying response discontinuities attributable to structural damage [1]. As the structural engineering field progresses towards performance-based design principles, structural monitoring systems can provide extensive empirical data that can be used to refine building codes and improve nonlinear structural models. Structural monitoring can provide building owners with rapid insight to the level of seismic excitation exerted on their structures, identify if their structures are safe for occupants following an earthquake and what can be done to improve structural integrity for long-term risk management [2].

The current California Building Code (CBC), based upon the 1997 Uniform Building Code (UBC), recommends installation of structural monitoring systems in structures situated in zones of high seismic activity. A minimum of three accelerometers are suggested for buildings with dimensions of six or more stories and total floor areas greater than 5,500 square meters [3]. This CBC/UBC instrumentation recommendation is insufficient for high-rise structures where structural models are characterized by high frequency modes with strong participation factors [4]. In addition to buildings, long-span bridges and dams have been instrumented with monitoring systems to measure their responses to earthquakes. In California, over 900 sensing

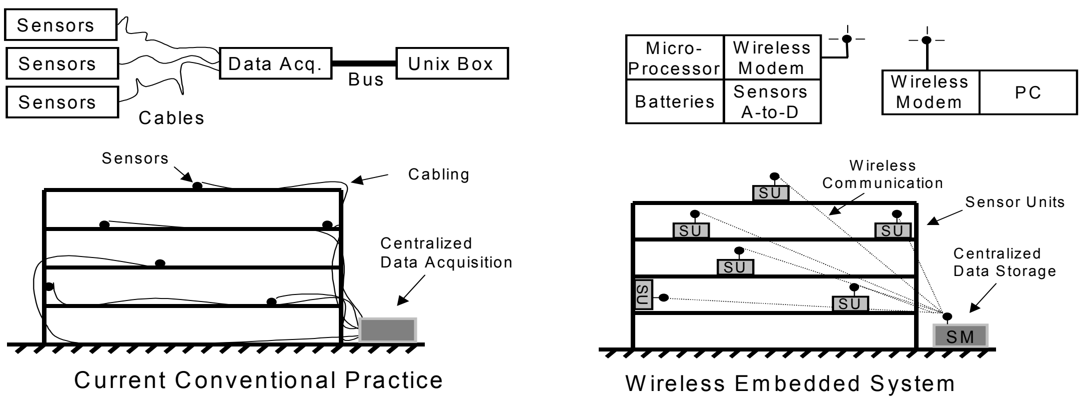

Figure 1 – Wire-based versus wireless structural monitoring systems

channels have been installed on 60 long-span bridges by the California Department of Transportation and over 100 dams have been instrumented by the California Division of Safety of Dams [5, 6]. Internationally, structural monitoring systems have been instrumented in a broad class of structures. The Tsing Ma suspension bridge in Hong Kong was instrumented with 350 channels upon construction completion in 1997 [7]. In Europe, structural monitoring systems employing fiber optic strain gages are often embedded in concrete bridges to measure long-term deflections [8].

Commercially available structural monitoring systems employ hub-spoke system architectures where remote sensors are wired directly to centralized data acquisition systems as shown in Figure 1. Typical sensors used to record environmental loads and structural responses include accelerometers, strain gages and anemometers. In current systems, sensors lack the means to process their data and are only responsible for communicating the measurements taken. Therefore, the centralized data server is responsible for the aggregation, storage and processing of all measurement data.

Today, the cost of installing structural monitoring systems in civil structures can be characterized as high. For example, structural monitoring systems installed in buildings can cost $5,000 per channel with typical installations using 12 sensing channels, resulting in total system costs of over $60,000 [4]. Fiber optic monitoring systems installed in concrete bridges can cost between $20,000 and $100,000 for spans greater than 200 meters [9]. The expensive nature of structural monitoring systems is a direct result of the high installation and maintenance costs associated with system wires. For example, installation of the monitoring system can represent up to 25% of the total system cost with over 75% of the installation time focused solely on the installation of system wires [10]. In outdoor applications such as bridges, potentially harsh environmental conditions necessitate additional efforts to install system cables in weatherproof conduits thereby raising installation costs.

As a result of high installation and maintenance costs, the adoption of structural monitoring technologies in the marketplace can be characterized as sluggish. Thus far, only structures identified as critical can justify the expenses associated with installing a structural monitoring system. As a consequence of hub-spoke architectures, structural monitoring systems have poor scalability properties with systems comprised of hundreds of sensors becoming increasingly expensive on a per channel basis. Today, there is a growing demand for structural monitoring systems because they represent an enabling technology for a broader set of applications. In particular, researchers have been successful in developing computational algorithms that can be used to identify the existence of damage in structures [11]. The computational demands of engineering analyses, such as damage detection procedures, can be high. With engineering analyses ordinarily performed by the centralized data acquisition unit, the centralized monitoring system can becomes overburdened with computational tasks.

To address the cost and performance shortcomings of current cable-based structural monitoring systems, use of advanced embedded system technologies is proposed to reduce monitoring system costs while simultaneously providing additional functionalities. The use of wireless communications to transfer sensor measurements to a centralized data acquisition system was first proposed by Straser and Kiremidjian [10]. Their work was instrumental in proving the reliability and cost-effectiveness of wireless communications in lieu of extensive cabling in a structure. More recently, Lynch *et al.* have extended their work to couple computational power in the form of low-cost microcontrollers with each wireless sensor node [12]. The intended purpose of integrating computational power directly with the sensor is to permit localized execution of embedded engineering analyses locally. Many benefits can be reaped from a wireless monitoring system with embedded computational power. First, decentralization of computational power permits an efficient infrastructure for parallel processing of data. Second, with wireless radios consuming large amounts of power, processing data at the sensor and transmitting only the results reduces the quantity of raw time-history data. Limiting the use of the wireless radio improves the power efficiency of the wireless structural monitoring system. The power efficiency of the wireless monitoring system is of primary concern because portable batteries of finite operational duration represent a likely power source for each sensor node.

Research and development efforts in both academia and industry have produced wireless sensing networks for a variety of applications. The Smart Dust and μAMPS projects have both yielded low-cost wireless sensor nodes designed for deployment in wireless sensor networks define by high nodal densities [13, 14]. With short communication ranges, embedded firmware is used to manage the flow of measurement data in these sensor networks by multi-hopping. Commercial wireless sensor platforms are also commercially available from Crossbow and Microstrain [15, 16]. However, the systems developed do not address the unique demands of the structural monitoring domain where low-power consumption characteristics of a wireless sensing platform are to be balanced by far-reaching communication ranges and sufficient computational capabilities for autonomous data processing.

The objective of this research is to develop a state-of-the-art wireless sensing unit that can be used as the fundamental building block of a wireless modular monitoring system (WiMMS) that is proposed for civil structures. The research aims to develop an optimal hardware design that is low-cost, low-power yet functionally comparable to current cable-based structural monitoring systems. Embedded intelligence of the wireless sensing unit is in the form of a sophisticated dual-processor core design that can be used for localized data interrogation. Interrogation of data directly at the sensor node reduces the demands on the wireless radio thereby preserving the life span of portable power supplies. To illustrate the strength of the computational core, a computational task is embedded in the sensing unit and executed on raw time-history data obtained from a simple lumped mass laboratory test structure. The embedded analysis chosen for this study is a two-tiered time-series damage detection procedure based upon a statistical pattern recognition paradigm. The paper concludes with a brief discussion of current research efforts to embed a broad class of algorithms in the wireless sensing unit aimed towards compression of data. Reduced data flow can be attained using both lossless and lossy data compression techniques thereby reducing the wireless channel usage.

A WIRELESS SENSING UNIT OPTIMIZED FOR STRUCTURAL MONITORING

A proposed wireless sensing unit is designed as the cornerstone component of the proposed wireless structural monitoring system [17, 18]. At the outset of the design process, functional requirements of the sensing unit are specified that reflect the demands of structural monitoring. First, low-power consumption characteristics of the wireless sensing unit are sought to ensure long lasting autonomous operation before battery replacement is required. Furthermore, the range of the wireless communication channel must be on the order of a hundred meters to permit sufficient separation of the units in large scale structural systems. Wireless radios with far range exhibit superior propagation properties within enclosed structures such as buildings and dams. A low cost wireless sensing unit is sought thereby encouraging installation of structural monitoring systems defined by high sensing densities.

A modular approach is taken in the design of a wireless sensing unit for application in a wireless structural monitoring system. Principally, the design of the sensing unit can be divided into three functional modules: sensing interface, computational core, and wireless communications. A modular design approach results in a sensing unit that can easily be upgraded as embedded system technologies continue to mature. In addition, dividing the sensing unit design into functional categories favors optimization of each module with respect to cost, desired functionalities and power consumption characteristics.

Sensing Interface

A plethora of sensors can be used to measure the environmental loading and response of structural systems. The wireless sensing unit should be capable of permitting easy interface of traditional sensors such as accelerometers and strain gages as well as new sensors potentially relevant to structural monitoring applications. A sensor transparent interface is designed with multiple channels to accommodate sensors with both analog and digital outputs. A multi-channel interface supports multi-sensor data fusion where the outputs of some sensors are used to attain accurate calibration or enhancement of another [19].

A single-channel 16-bit analog-to-digital (A/D) converter is chosen to accommodate sensors with analog outputs. With a maximum sampling rate of 100 kHz, the Texas Instruments ADS7821 A/D converter can even be used to collect local structural member responses whose dynamics are defined by high-frequency modes. At the maximum sampling rate of 100 kHz, the converter draws 16 mA of current. For lower sampling rates (20-200 Hz), the current draw of the A/D converter will be on the order of 1 mA. Two additional sensor channels are provided for sensors with digital outputs. In total, three sensor channels are provided by the sensing interface.

Computational Core

The most important component of the proposed wireless sensing unit design is the computational core. Core responsibilities include overall operation of the wireless sensing unit in addition to processing of acquired time-history data. The core is comprised of embedded microcontrollers and their appropriate support circuitry. Commercial microcontrollers come in different sizes (internal bus size), speed, and costs. Low-power microcontrollers tend to be found in 8-bit architectures. While such microcontrollers could easily accommodate the operation of the sensing unit, computationally intense engineering analyses embedded in the core would be difficult to implement. To address the need for high analysis throughput, higher end microcontrollers, namely 16- and 32-bit architectures, are required. Unfortunately, the power consumption characteristics of 16 and 32-bit microcontrollers exceeds design requirements and would drain portable power supplies rapidly. A balance can be attained by designing a computational core with dual processors: a low-power 8-bit microcontroller for overall unit operations and a 32-bit microcontroller for execution of embedded engineering analyses. Normal operation of the wireless sensing unit would rely upon the 8-bit microcontroller. When data is ready for processing, the 8-bit microcontroller would turn the 32-bit microcontroller on and command it to interrogate the data. Upon completion of the prescribed analyses, the 8-bit microcontroller will record the results and turn the 32-bit microcontroller off.

A low-power 8-bit microcontroller is selected for control of the data acquisition operation of the wireless sensing unit. In particular, the Atmel AVR AT90S8515 microcontroller is chosen [20]. By leveraging the internal services provided by the AT90S8515, reliable acquisition of sensor data from the sensing interface can be performed in real-time. The wireless communication channel is directly accessed through the AT90S8515's serial port. With memory and computational speed limited on the AT90S8515, a second microcontroller is selected for inclusion in the computational core. The Motorola MPC555 PowerPC, a high-performance 32-bit microcontroller, is selected for the task of local data interrogation [21]. With significantly more read only memory (ROM) and random access memory (RAM) onboard, in addition to a faster clock rate of 20 MHz, intensive data processing not possible on the AT90S8515 can now be performed. The AT90S8515 (at 4 MHz) draws 8 mA of current when turned on and active while the MPC555 (at 20 MHz) draws 110 mA. When placed in sleep mode, both microcontrollers draw reduced currents of 2.5 mA and 4 mA for the AT90S8515 and MPC555 respectively.

Wireless Communications

In exchange for reliable cable-based communications, a low-cost and flexible wireless communication system is chosen. For installation in civil structures, wireless communication components must have node to node ranges of over 150 meters and employ spread spectrum techniques to ensure reliability in the face of channel interference, multi-path reflection, and path loss [22]. Furthermore, the wireless communications require adequate penetration characteristics through typical civil engineering materials such as heavily reinforced concrete [23].

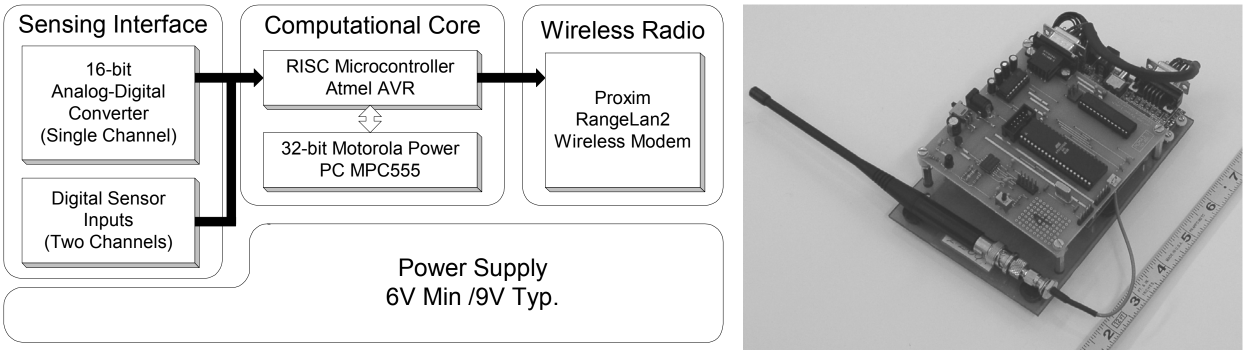

Figure 2. Wireless sensing unit design overview (left) and completed fabrication (right)

The Proxim RangeLAN2 7911 radio modem is selected to serve as the wireless technology for the sensing unit. Operating on the 2.4 GHz unregulated FCC industrial, scientific and medical (ISM) band, the RangeLAN2 communicates at a data rate of 1.6 Mbps. A standard RS232 serial port interface is provided by the modem for direct communication with the computational core. By employing a 1 dBi omni-directional antenna, open space communication ranges of over 300 meters can be attained which is a suitable range for the installation of sensing units on bridges. Unfortunately, the shielding behavior of heavy construction (e.g. concrete) reduces the range to approximately 150 meters when used on the interior of structures.

Powered by a 9 V direct current (DC) voltage source, the wireless modem draws 190 mA of current while actively receiving and transmitting. Compared to the power consumption characteristics of the computational core, the large power demands of the wireless modem provide additional motivation for performing as many data interrogations possible using the sensing unit. When the modem is not needed, its current draw can be reduced to 60 mA by placing it in sleep mode. Sleep mode is important for preserving the life of the unit's battery source.

Wireless Sensing Unit Construction and Validation

To house the chosen circuit components, a two-layer printed circuit board is designed and fabricated. The circuit board is designed to keep the wireless sensing unit form factor low and to ensure a low electrical noise environment. A limitation of the two-layer circuit board design is its inability to sufficiently separate analog and digital circuit components resulting in injected noise in the A/D conversion process. As a result, the effective resolution of the conversion is on the order of 13-bits [12]. The wireless sensing unit can be powered by a minimum 6 volt direct current (DC) power supply.

The completed wireless sensing unit, as pictured in Figure 2, has been previously tested and its performance validated in both the laboratory and field setting. Simple laboratory test structures have been used to successfully collect data from microelectromechanical system (MEMS) accelerometers in addition to locally calculate the frequency response function of time-history data [12]. The unit has also been taken to the field for instrumentation upon the Alamosa Canyon Bridge in southern New Mexico in parallel with a cable-based data acquisition system. The accuracy of the wireless monitoring system has been shown to be comparable to that of the commercial system. In addition, installation of the wireless sensing units on the bridge was completed in half the time required for the cable-based system [24].

Table 1 summarizes the operational life of the wireless sensing unit for two different battery cell chemistries. Typical alkaline (Zn/MnO_2 cell chemistry) and high energy density (Li/FeS_2 cell chemistry) 7.5 V battery packs are considered. Based on design charts provided by the manufacturer, the continuous operational life of the wireless sensing unit is calculated [25]. The RangeLAN2 wireless radio is powered separately from the rest of the wireless sensing unit. The operational lives listed are conservative because they assume continuous use of the batteries and do not reflect the batteries' ability to extend their lives through re-equilibrium of the cell during duty cycle usage. Furthermore, if unit volume is not an issue, additional battery packs can be placed in parallel to increase the unit's operational life before battery replacement is required.

Table 1. Wireless sensing unit operating life for various battery chemistries

Operational State	Current (mA)	5-AA L91 (Li/FeS_2) Battery Pack (7.5 V)	5-AA E91 (Zn/MnO_2) Battery Pack (7.5 V)
AT90S8515 On (MPC555 Off)	50	50 hours	30 hours
AT90S8515 On (MPC555 On)	160	15 hours	5 hours
RangeLAN2 Active	190	12 hours	3.5 hours

POWER EFFECIENCY OF LOCALIZED DATA INTERROGATION

Our proposed wireless monitoring system places a strong emphasis upon leveraging the computational strengths of the unit's core to first interrogate data and to communicate the results to adjacent wireless sensor nodes. Transfer of long records of measurement time-histories is not an efficient use of the wireless medium and should be avoided for real time communication when possible. Results derived from raw time-history data for communication to the wireless network could include modal frequencies, location and severity of potential structural damage and sensor status information.

The rationale for employing the wireless sensing unit's computational core to attain energy efficiency is best explained through the use of an example. Consider an operational scenario where the wireless sensing unit is used to collect a raw time-history record of 4096 points. Since each data point produced by the A/D converter is represented by a 16-bit integer, the resulting record is in total, 65,536 bits (8,192 bytes). The RangeLAN2 radio is capable of sending data packets with a maximum size of 1462 bytes (including 14 bytes of overhead per packet). As a result, the entire time-history record can be sent using 6 packets. At a communication baud rate of 19,200 bits per second, the wireless radio requires 4.3 seconds of time, t, to transmit the data during which time the radio draws 190 mA of current, i. The internal electrical circuit of the wireless radio is regulated at a voltage, V, of 5 V. Based on Equation (1), the total amount of energy, E, consumed by this operation is 4.09 Joules.

$$E = V \cdot i \cdot t = (5 \ \ V)\ (0.190 \ \ mA)\ (4.3 \ \ sec) = 4.09J \tag{1}$$

Consider the scenario where instead of transmitting the raw time-history record, the MPC555 microcontroller is used to execute an engineering analysis and the results transmitted. The MPC555 powered by a direct current power source and draws 110 mA of current. Internally, the MPC555 is regulated to a 3.3 V voltage. The time required, t_{MPC555}, for the MPC555 to consume the same amount of power as that used by the wireless radio in transmitting 4,096 point record is equal to 11.25 seconds ($t = E/V \cdot i$).

$$t_{MPC555} = E/(V \cdot i) = (4.09 \ \ J)/(3.3V \cdot 0.110mA) = 11.25 \ \ sec \tag{2}$$

In this assessment, the amount of energy expended by the wireless radio in transmitting results with sizes of 100 bytes or less is negligible. As a result, embedded engineering analyses that can be performed within 11.25 seconds represent a direct energy saving in the wireless monitoring system. As will be shown in this study, engineering analyses can easily be conducted within this allotted timeframe.

LOCALIZED EXECUTION OF DAMAGE DETECTION ALGORITHMS

Structural health monitoring entails the use of damage detection algorithms for the identification of damage in a structural system. 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. An extensive body of literature has illustrated the successes and failures of different damage detection algorithms that have been applied to a broad class of structural systems [26]. Early damage detection methods that relied upon modal properties and finite element representations of the structural system have been difficult to apply to civil structures because of normal environmental and operational variability associated with structures. As a result, a statistical time-series approach that does not require information of the system operational and environmental variability has been proposed for detecting possible damages in civil structures [27]. Statistical time-series approaches have been successfully applied to a laboratory test structure, the hull of a high-speed patrol boat and on a full-scale benchmark problem structure [28-30]. The time-series approach is designed for implementation with measurement data collected from a single node of the dynamic system. When the analysis is performed in parallel at various sensing nodes distributed throughout a structure, a spatial dimension to the approach can be exploited to assist in estimating damage locations.

The value of integrating embedded system hardware and engineering software in the proposed wireless sensing unit is made clear by the unit's potential use in an autonomous structural health monitoring system that employs statistical time-series approaches for damage detection. A two-tiered auto-regressive model approach can be implemented using the wireless sensing units. The autonomous nature of the approach does not require the direct exchange of raw time-history data between wireless sensing units further simplifying its implementation. A simple lumped mass laboratory test structure is used to illustrate and validate the autonomous execution of this promising damage detection procedure.

Statistical Time-Series Damage Detection Methodology

As proposed by Sohn *et al.*, the time-series analysis begins with measurement of the response, y, of the structure at a particular sensor location [29]. Assuming the response to be stationary, an auto-regressive (AR) process model is used to fit the discrete measurement data to a set of linear coefficients weighing past time-history observations:

$$y_k = \sum_{i=1}^{p} b_i^{\,y} y_{k-i} + r_k^{\,y} \tag{3}$$

The response of the structure at sample index, k, as denoted by y_k, is a function of p previous observations of the response of the system, plus, a residual error term, r_k^y. Weights on the previous observations of y_{k-i} are denoted by the b_i coefficients. A large number of AR models can be derived for an undamaged structure under a variety of operational conditions to populate a database consisting of AR model coefficients. If the structure is damaged, an AR model fit to time-history data would not be in agreement with the database models that correspond to the undamaged structure. Model agreement, D, is calculated by determining the Euclidian distance between coefficient vectors of the AR model calculated and those in the database. A lower distance between coefficient vectors suggests stronger agreement.

$$D = \sum_{i=1}^{p} \left(b_i^{DB} - b_i^{\,y}\right)^2 \tag{4}$$

It is assumed that the residual error of the AR model, r_k^y, is influenced by the unknown excitation input to the system. As a result, a second time-series model is chosen to model the relationship between the residual error and the measured response of the system. For this second model, an auto-regressive with exogenous inputs (ARX) model can be chosen [29]:

$$y_k = \sum_{i=1}^{a} \alpha_i y_{k-i} + \sum_{j=0}^{b} \beta_j r_{k-j}^{\,y} + \varepsilon_k^{\,y} \tag{5}$$

Coefficients on past measurements and the residual error of the AR model are α_i and β_i, respectively. The residual of the ARX model, ε_k^y, is a damage sensitive feature used to identify the existence of damage in the structure regardless of its operational state. Statistics of the ARX model residual error will then be used to hypothesize damage in the structure.

Implementation of the Two-Tiered Time-Series Damage Detection Method

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. Prior to using the raw time-history records, their means and standard deviations are standardized to zero and one respectively. After measuring the response of the structure, y_k, in an unknown state (damage 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 determined by minimizing Euclidian distance, D, of the newly derived AR model and the database AR models coefficients, b_i^y and b_i^{DB} 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 to determine the residual error, ε_k^y, of the ARX model:

$$y_k = \sum_{i=1}^{a} \alpha_i^{DB} y_{k-i} + \sum_{j=0}^{b} \beta_j^{DB} r_{k-j}^{y} + \varepsilon_k^{y} \tag{6}$$

The residual error 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, damage can be identified when the ratio of the standard deviation of the model residuals exceeds a threshold value established from good engineering judgment [29].

$$\frac{\sigma(\varepsilon^{y})}{\sigma(\varepsilon^{DB})} \geq h \tag{7}$$

Establishing a threshold, h, that minimizes the number of false-positive and false-negative identifications of damage is necessary for robust damage detection [29].

The wireless sensing unit will be used to embed the statistical time-series damage detection method presented. Given the memory limitations of the wireless sensing unit, storage of a database of AR and ARX coefficients is done using a remote data server. The implementation details using the wireless sensing unit are presented in Figure 3.

Embedded Firmware Development

An abstraction layering approach is taken for writing embedded software (also termed firmware) for the wireless sensing unit. The lowest layer of firmware is written to directly interact with hardware subsystems of the sensing unit thereby hiding implementation details from upper software layers. An upper software layer that sits upon the lowest layer is reserved for embedded engineering analyses. At both layers, the unique programming demands of the wireless sensing unit such as limited on-board program and data memory must be addressed to deliver an optimized program.

Software is required to determine the coefficients of an AR(p) model based on a segment of recorded time-history data. A least-squares approach can be taken to calculate the coefficients of an AR model. For calculation of the coefficients by the wireless sensing unit, Burg's approach to solving the Yule-Walker equations is chosen because it is proven to be more stable compared

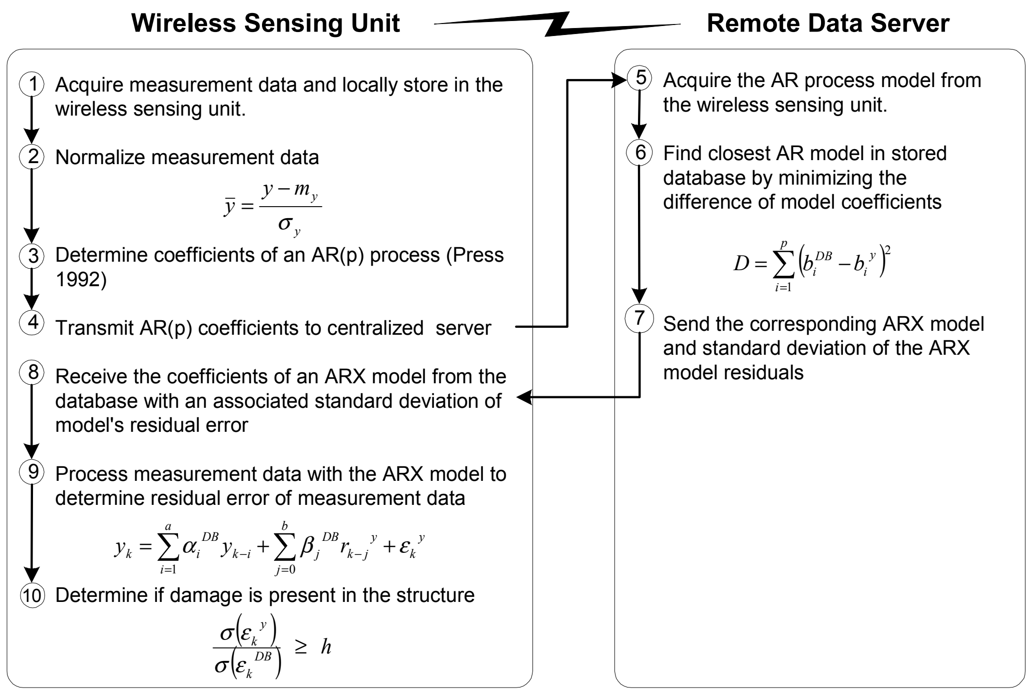

Figure 3. Implementation details of using the wireless sensing unit to autonomously detect damage

to least-squares by avoiding matrix inversions [31]. Multiplying Equation (3) by the current measurement sample, y_k, and taking the expected value of both sides of the equation, the autocorrelation function, φ, of the auto-regressive process is derived.

$$\varphi(k) = \sum_{i=1}^{p} b_i^{y} \varphi(k-i) \tag{8}$$

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:

$$\begin{bmatrix} \varphi(0) & \varphi(1) & \cdots & \varphi(p-1) \\ \varphi(1) & \varphi(0) & \cdots & \varphi(p-2) \\ \vdots & \vdots & \ddots & \vdots \\ \varphi(p-1) & \varphi(p-2) & \cdots & \varphi(0) \end{bmatrix} \begin{Bmatrix} b_1 \\ b_2 \\ \vdots \\ b_p \end{Bmatrix} = \begin{Bmatrix} \varphi(1) \\ \varphi(2) \\ \vdots \\ \varphi(p) \end{Bmatrix} \tag{9}$$

The coefficients of the auto-regressive 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.* for determining the coefficients of the auto-regressive model directly from the measurement data [31]. 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.

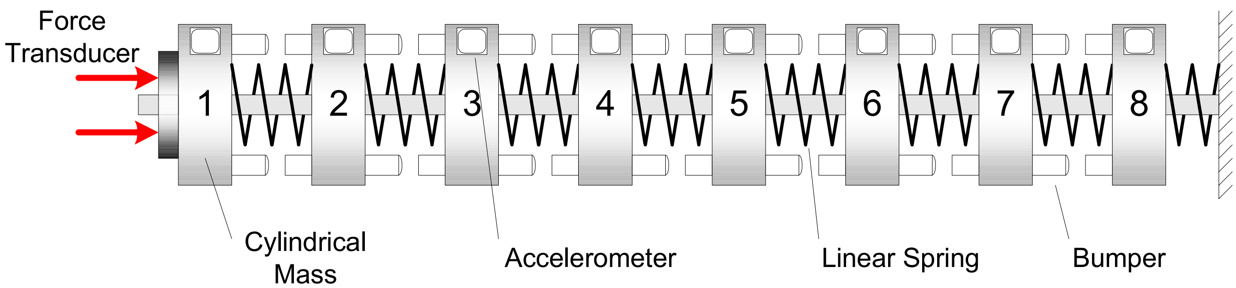

Figure 4. Laboratory test structure of eight aluminum disks excited by an external force transducer [28]

Laboratory Validation using a Lumped Mass Test Structure

Raw time-history measurements taken from previous testing of a lumped mass laboratory test structure is used to illustrate the successful execution of the embedded time-series damage detection procedure. The lumped mass model is comprised of eight cylindrical aluminum disks (25.4 mm thick, 76.2 mm diameter) that are free to slide along a common steel rod with coil springs placed between adjacent masses. Each aluminum disk is 419.4 g, except for the first whose mass is 559.3 g, and the spring constant of the coil springs is 56.7 kN/m. Structural damping is derived from Coulomb damping between the aluminum disks and the steel rod. Endevco 2251A-10 accelerometers are firmly attached to each mass of the system to measure transverse acceleration responses from input excitations imparted by a 215 N electro-dynamic shaker. To induce damage to the structure, adjustable bumpers are placed between masses. To simulate damage in the structural system, bumpers are adjusted to ensure contact when the system is excited. This damage is analogous to the closing of a crack during vibration in a civil structure. A picture of the complete test setup is presented in Figure 4 with the aluminum disks numbered.

Sohn and Farrar have extensively used the laboratory test structure to test the proposed time-series damage detection method [28]. In their study, a cable-based laboratory data acquisition system was used to collect the acceleration response of the system to white-noise excitations of prescribed standard deviations. Their time-history records are 4096 points in length and have been collected at a sampling rate of 512 Hz. The response time-history records collected by their study are stored in the wireless sensing unit and will be used by the embedded damage detection analysis. Because the focus of this study is to validate the accuracy of the wireless sensing unit in executing embedded algorithms, use of their data set is justified even though it has not been collected by the wireless sensing unit sensing interface.

For both the undamaged (no bumper) and damaged (bumper) states of the structural system, the force transducer is set to exert forces at two operational levels (white noise forcing functions characterized by standard deviations of 26.6 N and 31.1 N). Using response data obtained from the undamaged structure, a database of AR(30)-ARX(5,5) model pairs is populated. Selection of 30 coefficients for the AR model is determined from where the autocorrelation function of the response is below a certain threshold near zero. Likewise, the dimensions of the ARX model are chosen to be smaller than the dimension of the AR model as recommend by Ljung [32].

Damage in the structural system is modeled by adjusting the bumper between selected masses to ensure contact during the external excitation [28]. The bumper on the first mass is adjusted to induce contact between mass 1 and 2. The complete two-tiered time-series analysis embedded in the wireless sensing units is locally executed. Table 2 documents the results of the analysis with the ratio of standard deviations of Equation (7) presented. As presented in Table 2, damage is easily identified by the peak in the standard deviation ratio for the data processed in the vicinity of mass 2. The computational core embedded in the wireless sensing unit has successfully determined the possible existence and location of damage in the system.

Table 2. Analysis results of the damaged lumped mass structure (damage induced between mass 5 and 6)

Operational State	$\sigma(\varepsilon^{y})/\sigma(\varepsilon^{DB})$							
	Mass 1	Mass 2	Mass 3	Mass 4	Mass 5	Mass 6	Mass 7	Mass 8
Excitation σ = 31 N	1.0196	2.5181	1.3289	1.1240	1.1170	0.9780	1.0249	1.0401
Excitation σ = 31 N	1.0034	2.4547	1.2561	1.0320	1.0961	1.0022	1.0116	1.0050
Excitation σ = 31 N	0.9989	2.4823	1.3454	1.0820	1.0942	0.9799	1.0272	0.9996
Excitation σ = 26 N	1.0053	2.3187	1.2603	1.1133	1.0876	1.0605	1.0330	1.1117
Excitation σ = 26 N	1.0039	1.9954	1.0219	0.9573	0.9765	1.0209	0.9873	0.9875
Excitation σ = 26 N	1.0173	1.9762	1.1441	0.9707	1.0533	1.0463	1.0053	1.0021

With respect to energy efficiency, the time to calculate 30 coefficients of an AR model from 4096 data points is completed by the wireless sensing unit in 8 seconds. As previously discussed, a processor time of 11.25 seconds is required by the MPC555 to consume an equivalent amount of energy as sending 4096 data point with the wireless radio. As a result, an energy savings of approximately 30% has been attained by locally processing data. The current wireless sensing unit prototype is using low-power external random access memory (RAM) with a slow read-write time, adding latency in the embedded engineering analysis. Energy efficiencies can be drastically improved for this system by judiciously selecting a faster external RAM with accelerated read-write times. For example, to determine 30 AR coefficients from 1600 data points using the limited internal RAM of the MPC555, only fractions of a second are required.

EMBEDDING ADDITIONAL ENGINEERING ANALYSES

A wide variety of engineering analyses can be embedded in the proposed wireless sensing units. Previous work has explored embedding fast Fourier transforms in the wireless sensing units to derive the frequency response function of structural systems from raw time-history data. The frequency response function calculated by the wireless sensing unit has been used to estimate the modal frequencies of the Alamosa Canyon Bridge in New Mexico [24].

To reduce the flow of data in a wireless sensor network, data compression algorithms are currently being explored for use by the wireless sensing units. Data compression can allow more efficient time sharing of the limited wireless sharing in addition to saving operational power. Data compression can be of a lossless or lossy type. Lossless data compression exploits redundancy in data records without sacrificing the integrity of the data. On the other hand, higher compression rates can be attained through use of lossy compression techniques where data integrity is not assured. Both lossless and lossy data compression methods are being explored for embedment in the wireless sensing unit. At the center of this work is the use of wavelet transforms in both techniques. Inclusion of wavelet transforms for initial decorrelation of data samples is both computational efficient and easy to implement for execution by the computational core of the wireless sensing units. Wavelets are a valuable tool for compression in that they can attain higher data compression rates. In the realm of damage detection methods, wavelet transforms have also been illustrated to be a useful tool in identifying time-history discontinuities attributable to structural damage [33]. As a result, a common set of orthogonal basis functions is being sought that can be suitably used for both compression and damage detection methods.

CONCLUSIONS

The development of a wireless sensing unit for deployment in future structural monitoring systems is presented. A major innovation of the proposed unit is the inclusion of wireless communications and embedded microcontrollers. Wireless communications eradicates a need for expensive cabling in a structure while microcontrollers facilitate localized processing of raw time-history data prior to transmission in the wireless network. Distributing computational power throughout the sensor network in this manner attains high energy efficiency thereby preserving portable battery operational lives.

This study has focused upon illustrating the performance of the wireless sensing unit computational core by embedding a promising approach to the damage detection problem: statistical pattern recognition damage detection approach using AR and ARX time-series. Details unique to implementation in the limited resource microcontroller are addressed. An eight degree-of-freedom laboratory test structure, whose response data is readily available, is used. Damage is simulated in the test structure through installment of bumpers between the lumped masses to initiate contact during the system response to external excitations. The wireless sensing unit is configured for autonomous execution of the embedded damage detection algorithm. The test has conclusively shown the accuracy of the unit in identifying damage with a 30% energy savings as compared to wirelessly transmitting the raw time-history data.

Plenty of opportunity exists for extending this work to encompass additional embedded algorithms for localized execution in the wireless sensing unit. Data compression methods hold promise in reducing the amount of data transmitted over the wireless network between wireless sensor nodes. Investigation of lossless and lossy compression methods is currently underway. Additional damage detection methods can be explored for embedding as well as system identification methods.

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