



HEALTH MONITORING USING WIRED, WIRELESS AND HYBRID ARCHITECTURES

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Abstract

In this study, the authors chronicle their experiences using wired, wireless and hybrid sensor networks to monitor the health of civil infrastructure and the surrounding built environment. Particular emphasis is given to the limitations and benefits of these three architectures and the tradeoffs required in their full-scale application. The study then provides examples of the performance of hybrid sensor networks and the centralized and decentralized damage detection frameworks that have been applied in these architectures.

Keywords: Structural Health Monitoring, Damage Detection, System Identification, Wireless Networks, Civil Infrastructure.

Introduction

Outside of the healthcare industry, Civil Infrastructure Systems (CIS) are the largest societal investment, yet unlike its counterpart, CIS rarely employs advanced evaluation and diagnostic technologies. In fact, the United States CIS has been progressively deteriorating and continues to be assessed only sporadically and qualitatively using visual inspection, which is not only labor-intensive but also subjective and effective only in detecting surface defects. As a result, many forms of damage are not intercepted in their early stages or are obscured all together. This reality has driven the development of automated, unattended diagnostic capabilities broadly categorized as Structural Health Monitoring (SHM), which have the potential to remotely quantify levels of damage in its early stages.

Thanks to continued advances in hardware, a wide variety of monitoring systems and architectures have been introduced, each with inherent assets and limitations that place unique constraints on data processing and system identification. This paper will focus on the authors' experiences in developing and deploying three different system architectures to monitor civil infrastructure, with examples of damage detection schemes applied therein.

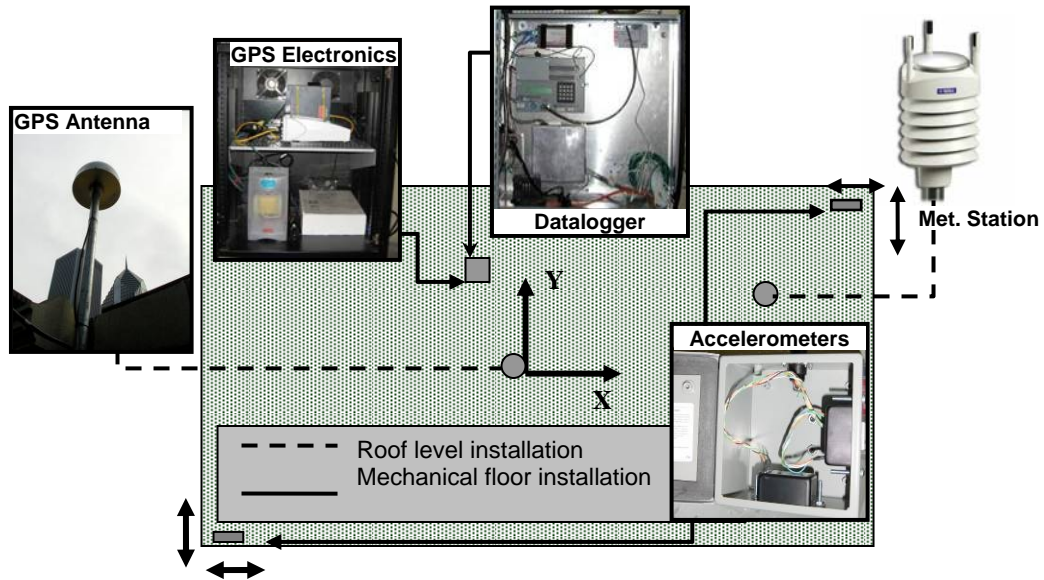


Figure (1): Schematic overview of wired acquisition system used in CFSMP.

Viable Architectures

It should be first acknowledged that the architectures utilized in this research rely solely on ambient excitations, since controlled excitations are not practical for many in-service structures due to disruption and cost. While this complicates subsequent diagnostic efforts, it does create monitoring schemes that may be received more favorably by owners.

Wired

The traditional approach to monitoring leverages the wired, “hub-and-spoke” architecture, where continuous data streams feed back into a centralized server or datalogger with a dedicated power supply and relatively robust computational resources enabling the synchronization of even hundreds of channels. Although data transmission is quite reliable, the installation effort and costs of running cables through large CIS can be prohibitive and depending on environmental factors, may require dedicated conduits, extensive shielding, and long-term repair/replacement. Furthermore, despite the isolation measures employed, the long cables generally required are prone to infiltration by noise. Still, the reliable transmission and archiving of data in these systems and the flexibility surrounding the system identification approaches that can be employed make them the mainstay of SHM.

The authors used this architecture for all the buildings instrumented through the Chicago Full-Scale Monitoring Program (CFSMP) (Kijewski-Correa et al., 2006a), integrating dataloggers interrogating an array of servo-force-balance analog accelerometers and ultrasonic anemometers/meteorological stations, complemented by global positioning systems (GPS). Figure 1 summarizes these sensor arrays on a generic floor plan. Of most important note is the stability of the configuration, being in continuous operation since 2002 with only one upgrade and maintenance operation in five years’ time.

Wireless

The concept of ubiquitous sensing has been made possible by advances in wireless communications and embedded processing to enable two classes of wireless systems: *wireless communications systems*, where single or multi-hop wireless transmissions replace the cables in the traditional hub and spoke architecture, while all computation remains localized at the central hub, and *wireless embedded sensor networks*, where much of the data processing is done locally at the sensor using a compact embedded microprocessor and only key parameters are then transmitted wirelessly to a data server. Regardless of the format, systems that are wireless are cheaper to install and maintain than wired systems for large CIS. Although issues of synchronization and packet loss can be mitigated both in the network protocols and in the data processing schemes, the primary limitation is power. Still the flexibility and scalability of wireless networks are compelling reasons to invest in future research regarding power scavenging and low power operating modes.

There have been considerable strides made in wireless networks, e.g., Lynch et al. (2004). In Kijewski-Correa et al. (2006b), the authors present their remedies to a number of practical challenges. All viable forms of damage detection rely on undamaged data to identify a reference condition for assessment. This reference pool must encompass a wide range of operational and environmental conditions to avoid false positives. The authors address this issue through the use of *Restricted Input Network Activation Scheme (RINAS)*, acquiring data only when environmental sensors and cameras indicate a target loading condition. While this does not allow the input to be explicitly measured or controlled, it does allow the operational and environmental states to be restricted to a specific subset for which a reliable reference pool has been generated. This reduces the size of the reference pool, thereby easing computational burden and memory demands. Furthermore, this form of event triggering helps to increase network lifetime. The secondary advancement offered is the use of heterogeneous sensing (strain and acceleration) and a tiered architecture that performs system identification at the node using embedded processors and then performs data fusion at multiple tiers within the network to enhance reliability (Kijewski-Correa et al., 2006c). Strict synchronization is not required and power demands are minimized.

The hardware leveraged in this wireless architecture, the Chasqui Wireless Mote (Fig. 2a), has been developed by a corporate partner, EmNet LLC. The mote includes 2MB of data storage, a 115kbps, 900MHz, 1W, FHSS radio, and is compatible with TinyOS. This platform has been used for a wide range of monitoring applications, including a new project that employs wireless networks of chemical detectors and meteorological stations (see Fig. 2b) that fuse data with a condensed computational fluid dynamics model to determine the real-time evolution of toxic plumes resulting from an urban chem-bio attack.

Hybrid

To mitigate the issues of packet loss, synchronization and more importantly power constraints, while preserving a “wireless” architecture to permit high sensor density, a third architecture has been developed for use in buildings. The “hybrid” wireless sensor concept emulates the traditional centralized data acquisition system but is wireless in that it replaces

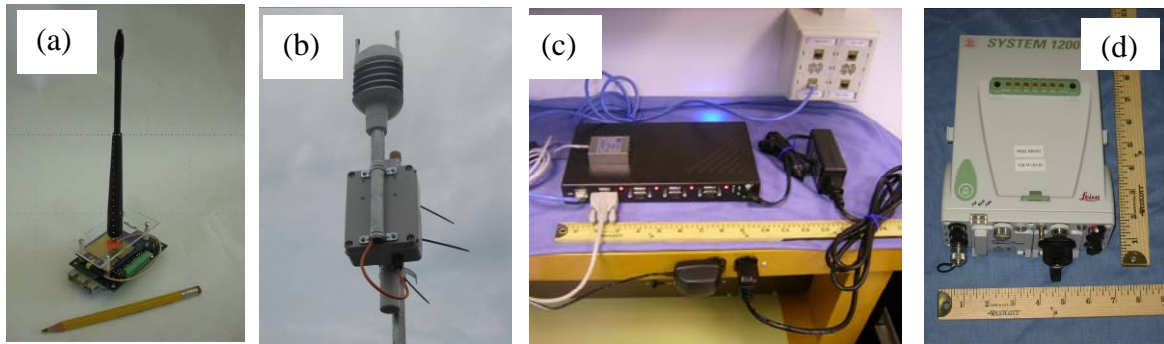


Figure (2): (a) Chasqui mote and (b) deployed met station interfaced with Chasqui mote (Courtesy of EmNet LLC); (c) hybrid system: digital accelerometer and (d) GPS receiver.

lengthy cable runs with existing Ethernet and power systems. This enables a plug-and-play approach through the use of digital sensors that connect to the local area network (LAN) using a direct serial interface, eliminating the need for analog filtering and digitization. The system shown in Figure 2c can be installed in lightweight enclosures and affixed at any location where power and a network connection are readily accessible. The serial interface shown in Figure 2c can accommodate up to four, digital biaxial devices. This mitigates much of the installation cost and effort of traditional wired systems and in many cases is more stable (with respect to power and communications) than wireless systems, given the high bandwidth and reliability of modern high speed connections. The hybrid architecture does require a centralized hub or server on the same subnet to synchronize and assimilate the outputs streaming from the various sensors distributed over the LAN. This server operates as a gateway, hosting a secure website with real-time output displays. The ability to achieve successful synchronization and data aggregation in this “wireless” hub-and-spoke architecture depends very much on the available bandwidth, sampling rate and the number of sensors on the LAN. Despite these constraints and the vulnerability to network outages, the flexibility of this system is an asset, making it viable for use in buildings.

Currently, the primary limitation for this hybrid architecture is the availability of high-sensitivity, affordable digital sensors. The authors have currently deployed hybrid architectures using biaxial digital accelerometers (Fig. 2c) and Leica 1200-series GPS receivers (Fig. 2d), where the latter has performed well real-time kinematic tracking in full-scale over disparate LANs across state lines. The hybrid accelerometer network also demonstrated no comparable loss of quality when transferring data over LAN as opposed to direct hardwiring. This was established through a series of controlled shaker experiments. In fact, the average percent difference between the actual motions generated by a controlled shaker experiment and the measured accelerations by the biaxial digital accelerometer using LAN were 9% (RMS) compared to the average 12% (RMS) error observed using a hardwired digital accelerometer. An example is provided in Figure 3.

Architecture-Specific System Identification

Centralized

System identification approaches have traditionally targeted the extraction of modal properties (frequency, damping and mode shape) from measured response data. An

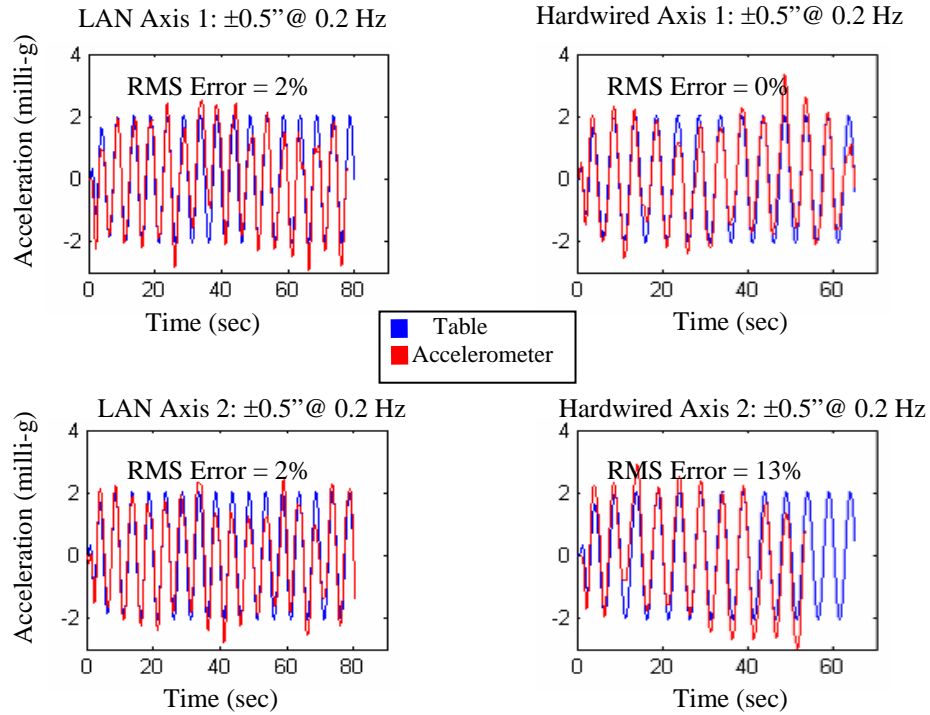


Figure (3): Comparison of controlled shaker accelerations to measured accelerations for the digital accelerometer (LAN vs. Hardwired).

overview of techniques successfully applied to buildings in full-scale, particularly in the United States, was previously presented by the authors (Kijewski-Correa and Cycon, 2007; Kijewski-Correa et al., 2008). As discussed therein, there have been very isolated attempts at full-scale damage detection in buildings, generally limited by the fact that relatively large sensor densities are required to identify and localize damage in complex systems. The system identification approaches that have been employed implicitly require hub-and-spoke architectures, where all acquired data is perfectly synchronized, fused and processed at a central hub with abundant computational resources and memory. Indeed the computational resources for system identification and damage detection in wired or hybrid network architectures are virtually limitless. As a result, more computationally intensive transforms and techniques can be employed. For example, Kijewski-Correa and Kareem (2004) utilized an analytic wavelet instantaneous frequency spectrum to document permanent stiffness losses in the Sherman Oaks Building in the 1994 Northridge Earthquake. Though this constituted a large level of damage, the transform has shown similar utility in feature extraction of much lower damage levels. A two stage algorithm using continuous wavelet transforms and principal component analysis (PCA) was applied to a simulated system (Case 1) undergoing amplitude-dependent crack opening and closing leading to minor (<1%) losses in stiffness. As suspected, the first principal component (PC), with analogs to the instantaneous frequency, showed negligible sensitivity to damage. However, the second principal component showed enhanced sensitivity, as demonstrated by the PC scores in Figure 4a, much like the sensitivity noted in instantaneous bandwidth. Furthermore, it was shown that the area formed by the two component scores increases with damage level, as demonstrated by the results in Figure 4b for Case 2, where damage

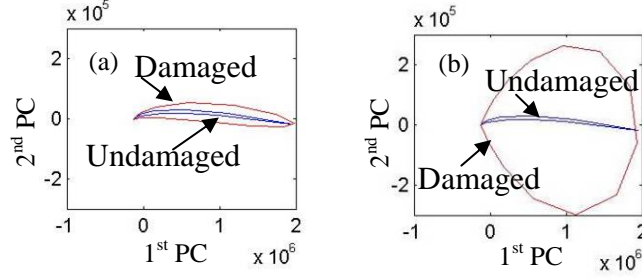


Figure (4): 1st and 2nd Component Scores for (a) Case 1; (b) Case 2.

levels were increased to 1% stiffness lost. While this can be as a damage sensitive feature (DSF), the computational effort required is not feasible for every network architecture.

Decentralized

The use of on-board processors requires recasting the system identification framework into a decentralized mode. Within in this construct, the algorithms used for feature extraction and damage detection must be relatively simple and efficient. This research adopts the general concept first introduced by Sohn et al. (2000) using regressive models for data condensation and statistically significant deviations of key metrics as indicators of damage. There have been a variety of autoregressive (AR) models utilized for data condensation of homogenous (acceleration only) data (Sohn et al., 2000; Nair et al., 2006). In all cases, model orders must remain relatively modest (~ 20) due to the computational constraints of the wireless platform. In this research, a *bivariate autoregressive (BAR) model* is employed to exploit the unique information carried in measured acceleration (A) and strain (S) data:

$$\tilde{A}(n) = \sum_{i=1}^{Na} \alpha_i A(n-i) + \sum_{j=0}^{Nb} \beta_j S(n-j) + \zeta(n) \quad (1)$$

where α_i is the i^{th} AR acceleration coefficient, β_j is the j^{th} AR strain coefficient, Na and Nb are the respective orders of the acceleration and strain representations, and ζ is the residual error. It was subsequently shown that this BAR representation provided an effective means for data condensation (Su and Kijewski-Correa, 2007a).

There have been a wide range of DSFs proposed in the literature. In some cases, certain AR coefficients (e.g., 1st or 2nd) are retained for this purpose (Nair et al., 2006). This can be considered a *static* DSF, in that the coefficients to be monitored are specified *a priori*. The authors have proposed an adaptive or *data-driven DSF* defined by the AR coefficient that deviates most significantly from the statistics of the reference pool. This can be cast in a homogenous (acceleration only) or heterogenous (strain and acceleration) form, as shown:

$$DSF = \max \left[\left| \frac{\alpha_i - avg[\alpha_i]_{ref}}{std[\alpha_i]_{ref}} \right|_{i=1:Na}, \left| \frac{\beta_j - avg[\beta_j]_{ref}}{std[\beta_j]_{ref}} \right|_{j=0:Nb} \right] \quad (2)$$

Eq. 2 is termed a *Bivariate Regressive Adaptive Index (BRAIN)* for damage detection within a decentralized, wireless sensor network, where the notation *ref* indicates that these statistics are calculated over the entire reference pool. Two key features should be noted:

1) The BAR coefficients for each vibration signal in the reference pool do not need to be stored locally; only the mean and standard deviation of each coefficient are ultimately required. Thus only $2Na$ reference values are stored at each sensor node, which dramatically reduces not only the required on-board memory, but also any computation (and power drain) associated with the manipulation of a large reference database.

2) The DSF is unaffected by the choice of underlying model (AR, ARMA, BAR, etc.) and its heterogeneity (AR vs. BAR), unlike other “static” DSFs that are tied to or have been validated with only a specific model type or sensor in mind. Thus the DSF is truly adaptive and can be applied to a wide variety of underlying models.

The performance of BRAIN has been demonstrated on a number of simulations and benchmarks to determine its ability to intercept and localize damage in its early stages (Su and Kijewski-Correa, 2007 a,b). These validations have demonstrated first and foremost, the advantages of a data-driven DSF. Even when only acceleration (homogenous) data is used, damage detection rates increased from as low as 0-20% for a static, homogenous DSF to 50-100% for a data-driven, homogenous DSF, depending on the proximity of the sensor to the damage site and the amplitude of the response above the noise floor. These studies further demonstrated the advantage of using heterogeneous response data, demonstrating BRAIN’s ability to improve the consistency of detection to 100% near the damage location and then trailing off as one moves further from the point of damage. In addition, the ability to localize and document the severity of damage was also noted, as the DSF values increased with increasing damage level and proximity. Even with their enhanced sensitivity, data-driven DSFs show virtually no evidence of false positives.

Conclusions

In order to enhance the practical viability of structural health monitoring, a high density of sensors is required, which is often infeasible using traditional wired architectures. This study chronicles the authors’ work in developing wireless and “hybrid” networks to overcome many practical limitations of wired networks, providing specific examples of a digital accelerometer operating in a hybrid architecture without losses. The study then addresses strategies for ensuing damage detection, which must be capable of distinguishing actual damage from environmental and operational variability. First, a centralized, time-frequency approach for hub-and-spoke architectures was presented. This was followed by an application for wireless sensor networks using decentralized system identification approaches that can operate within the computational constraints of the platform. This strategy employed data-driven damage sensitive features drawn from bivariate autoregressive coefficients. However, the authors stress that, despite the successes to date and the continued advances in hardware, the efforts of the community need still focus on developing reliable damage detection strategies that can operate within the constraints of these and future architectures.

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