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BRAIN: A bivariate data-driven approach to damage detection in multi-scale wireless sensor networks

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Abstract. This study focuses on the concept of multi-scale wireless sensor networks for damage detection in civil infrastructure systems by first over viewing the general network philosophy and attributes in the areas of data acquisition, data reduction, assessment and decision making. The data acquisition aspect includes a scalable wireless sensor network acquiring acceleration and strain data, triggered using a Restricted Input Network Activation scheme (RINAS) that extends network lifetime and reduces the size of the requisite undamaged reference pool. Major emphasis is given in this study to data reduction and assessment aspects that enable a decentralized approach operating within the hardware and power constraints of wireless sensor networks to avoid issues associated with packet loss, synchronization and latency. After over viewing various models for data reduction, the concept of a data-driven Bivariate Regressive Adaptive INdex (BRAIN) for damage detection is presented. Subsequent examples using experimental and simulated data verify two major hypotheses related to the BRAIN concept: (i) data-driven damage metrics are more robust and reliable than their counterparts and (ii) the use of heterogeneous sensing enhances overall detection capability of such data-driven damage metrics.

Keywords: structural health monitoring; damage detection; wireless sensor networks; civil infrastructure.

1. Introduction

A number of interesting parallels and contrasts can be drawn between personal health monitoring and structural health monitoring (SHM). The two sectors they serve respectively constitute the two largest societal investments in the United States, both dealing closely with human life safety. Both hold in high priority the need to diagnose health or assess condition by evaluating measurements or observations against established benchmarks for healthy specimens with comparable demographics. In both, errant diagnoses can be catastrophic, arguably even more so with civil infrastructure due to the potential for multiple lives being impacted or even lost in a single event. Yet interestingly, the public understanding and discourse on the condition and maintenance of civil infrastructure systems lags considerably behind the subject of personal health care. In the meantime, the infrastructure system in the United States continues to deteriorate and is assessed only sporadically and qualitatively using visual inspection, which is not only labor-intensive but also subjective and effective only in detecting surface defects. This is in sharp contrast to the health care industry, where advanced diagnostic aids and quantitative testing have long been commonplace for internal health assessments. As a result, in civil infrastructure

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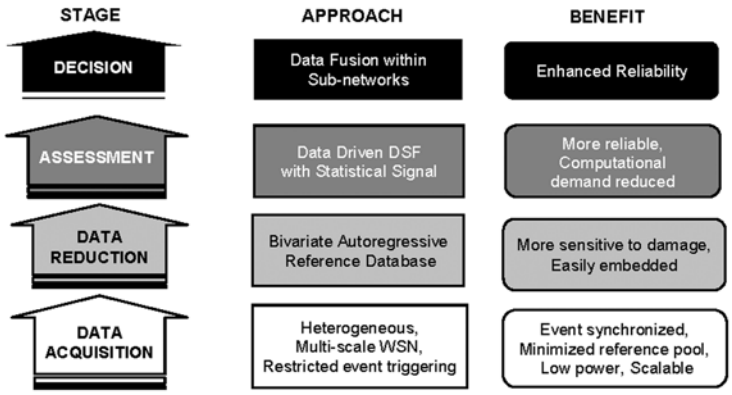


Fig. 1 Overview of key features of proposed wireless sensor network for structural health monitoring

many forms of damage are not intercepted in their early stages or are obscured all together. This reality has finally driven the development of automated, unattended diagnostic capabilities, which have the potential to remotely detect, locate, and assess the severity of any structural damage due to service loads, as well as extreme events, to enable more proactive maintenance.

As noted previously by a number of authors, the ease of installation and minimal intrusion on operations presented by wireless sensor networks makes them particularly attractive options for the concept of ubiquitous sensing, where much of the data processing is done locally at the sensor using a compact microprocessor and only key parameters are then transmitted wirelessly to a data server. 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 and the resulting power drain of excessive radio transmissions. Many applications in the last decade have affirmed that those networks utilizing this local processing capability embedded at the sensor node can considerably extend the network lifetime. Unfortunately, this often means that system identification frameworks originally intended for the classic hub and spoke architecture must be adapted or abandoned in favor of distributed identification schemes capable of reliably detecting damage using the limited on-board computational resources of the wireless motes and only the response data acquired at that location. With the goal of developing an effective WSN with decentralized processing, the authors and their colleagues proposed a wireless sensor architecture that featured a number of new attributes to extend lifetime and enhance detection capability (Kijewski-Correa, *et al*. 2006a). A summary of these attributes is provided in Fig. 1, each contributing in some way to the four stages of the health monitoring process: data acquisition, data reduction, assessment and decision making. Note that the primary focus of the present paper is the data reduction and assessment aspects; therefore, the in-network decision making and data fusion cannot be addressed here, but have been demonstrated by example in Kijewski-Correa, *et al*. (2006b).

2. Data Acquisition

Over the last decade there have been considerable advances in the use of embedded processing capabilities in wireless sensor networks. Early work in this area was led by Straser and Kiremidjian (1998) and advanced by subsequent prototypes, e.g. Wang, *et al.* (2005), with numerous other applications leveraging the MICA2 motes developed at the University of California at Berkeley (Hill,

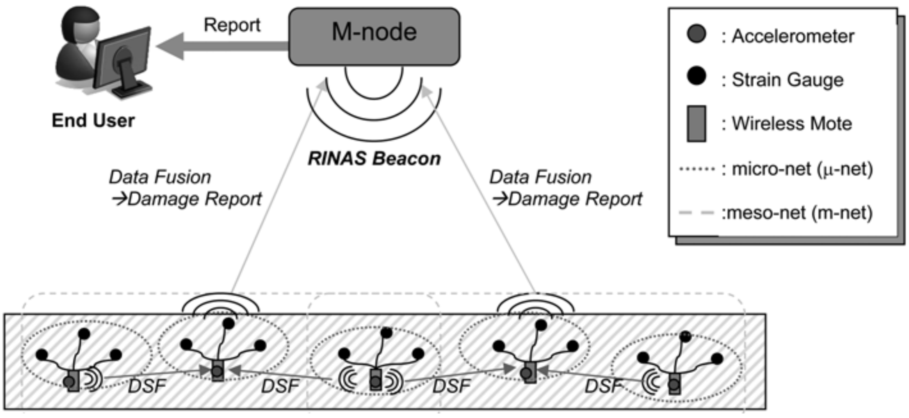


Fig. 2 Schematic of multi-scale wireless sensor network architecture

et al. 2000). Subsequently, key performance metrics such as maximizing network lifetime, enhancing reliability, and facilitating scalability have prompted a trend toward multi-scale network concepts (Mitchell, *et al*. 2002, Kottapalli, *et al*. 2003). Specifically, the multi-scale WSN introduced by Kijewski-Correa, *et al*. (2006a) divides the structure into a series of meso-networks (m-nets), as shown in Fig. 2. Within this m-net, there are wireless motes with on-board accelerometers tethered to multiple distributed strain gauges to monitor behavior at critical locations. Each accelerometer and their supporting strain gauges form a micro-network (μ-net), where the initial diagnosis of damage is conducted. This decentralized approach not only has power conservation benefits, but also escapes the need for strict synchronization and provides resistance to latency that a centralized approach to system identification would require. The only information shared outside of the μ-net is the binary damage diagnosis and estimated damage sensitive feature (DSF), which is a customized metric for rating damage presence, severity and location.

Unlike many networks that rely on sentinels for triggering the network, this system remains dormant, conserving power until the signal to collect data is initiated by a central marco-node (M-node). Thus this system is cycled to perform regular inspections when approaching traffic and environmental conditions meet specified criteria. Traffic classification can be accomplished through the use of camera or weigh-in-motion systems and environmental conditions can be established through any class of meteorological station all operating at the M-node. Again since ambient vibration monitoring is being employed, to minimize disruption, the input to the bridge is never explicitly known or controlled. However, the use of a *Restricted Input Network Activation Scheme (RINAS)*, acquiring data only when a target loading condition is satisfied, does not allow the input to be explicitly measured or controlled, but does allow the operational and environmental states to be restricted to a specific subset for which a reliable reference pool has been generated, e.g., the passage of a semi-trailer at night under a particular weather condition. This then reduces the size of the reference pool, thereby easing computational burden and memory demands. This M-node also serves as the network gateway, receiving information on structural condition and potential damage locations and severity wirelessly from the m-nets through multi-hop wireless communication and then interfaces with the end user to report the findings. The following sections address the data reduction and assessment that is conducted locally within each μ-net using only the network's distributed computational resources.

3. Data reduction

The use of on-board processors requires recasting the system identification framework into a decentralized mode. Within this construct, the algorithms used for data reduction and assessment must be relatively simple and efficient, leading the authors to adopt the general concept first introduced by Sohn, *et al*. (2000) using time-series regressive models for data reduction and statistically significant deviations of key metrics for the damage assessment mechanism. As deviations in model parameters constitute the primary mechanism of damage detection, the accuracy of the underlying models used for data reduction becomes quite important. Due to similar constraints, the DSFs employed, and discussed in the subsequent section, must also be simplified in nature, generally implying that they are specifically tailored for the underlying time series model, limiting their robustness and ability to be extended to other applications. In the discussions that follow, two classes of models will be discussed: *homogeneous* models, which consider only one type of response quantity, e.g. acceleration, and *heterogeneous* models, which consider multiple response quantities.

3.1. Homogeneous models

A few types of homogeneous regressive models had been used previously for the time-series characterization of vibration signals, beginning with the autoregressive moving averages (ARMA) formulation, where the k^{th} acquired vibration signal is represented at each time step n by na AR terms and nb MA terms[1]:

$$\tilde{A}_k(n) = \sum_{i=1}^{na} \alpha_{ki} A(n-i) + \sum_{j=0}^{nb} \beta_{kj} \zeta_k(n-j) + \zeta_k(n) \tag{1}$$

where α_{ki} is the ith AR coefficient, β_{kj} is the jth MA coefficient, and ζ_k is the residual error of the kth time series. Letting $\beta_{kj} = 0$ reduces this to an autoregressive (AR) representation. This will be categorized as homogeneous detection since a single type of response measurement, in most cases acceleration A, is used to characterize the system. The resulting model coefficients (α, β) can be used in damage detection, such as with the ARMA approach by Nair, *et al*. (2006), or the residual error ζ_k can be retained for damage detection, such as in the two-stage AR-ARX approach by Sohn, *et al*. (2000). In this approach, the residual error of an AR representation ($\zeta_{k,AR}$) acts as the exogenous input to a second stage na + nb order ARX model. While one of the primary merits of Sohn, *et al*.'s (2000) AR-ARX approach is its resistance to changes in the environmental and operational conditions of the system, as noted by Lynch, *et al*. (2004), local computational/memory capabilities within WSNs are often insufficient to execute the two stages of autoregressive-fitting, the database search required to find the appropriate reference state, the signal reconstruction and residual error estimation. For this reason, the RINAS approach introduced earlier in this paper is particularly advantageous, as it permits the use of a one-stage autoregressive model verified against a comparatively smaller reference pool without the need for signal reconstruction and residual error calculation.

3.2. Heterogeneous models

The use of a heterogeneous array in Kijewski-Correa, *et al*. (2006a) was motivated by the work by

[1]Note that in general, measured signals are standardized before a model is fit by demeaning and then normalizing by their standard deviation.

Law, *et al*. (2005), which demonstrated that the combined use of strain and accelerometer data outperformed the sole use of accelerometer data in damage detection using wavelet packets. Unfortunately, given the limited computational resources in the wireless platform, wavelet packets were abandoned and various formulations to model the interrelation between measured strain and acceleration were instead explored (Kijewski-Correa, *et al.* 2006b). In this study, specific focus is given to bivariate autoregressive (BAR) models between strain and acceleration, which have been used in a variety of disciplines for time series modeling of related quantities, including exchange rates within financial markets. In this representation, the k^{th} standardized strain and acceleration data pair (A, S) is fit by a na+nb order model:

$$\tilde{A}_k(n) = \sum_{i=1}^{na} \alpha_{ki} A(n-i) + \sum_{j=0}^{nb} \beta_{kj} S(n-j) + \zeta_k(n) \tag{2}$$

where α_{ki} is the i^{th} AR acceleration coefficient and β_{kj} is the j^{th} AR strain coefficient and ζ_k is the residual error. Note that a comparison of AR, ARMA, ARX and BAR representations was conducted by Su and Kijewski-Correa (2007a) and found that for the same effective model order, the BAR representation was found to be more accurate than its counterparts. The next section will now focus on damage sensitive features appropriate for regressive-type models.

4. Assessment using damage sensitive features

Once the acquired response time history is reduced using any of the aforementioned regressive-type models, an appropriate assessment metric or damage sensitive feature must be crafted using the resulting coefficients and/or residual error terms. Given the diversity of underlying models in the literature, it would be advantageous to offer a simple yet adaptive DSF that can accommodate various underlying models and even significant changes in the application, while still providing reliable detection.

Before discussing the various forms of DSFs, it is important to discuss how the issue of uncertainty is handled. In many practical health monitoring problems, the signals of interest exhibit some variability not due to damage, but rather due to changes in the environmental and operational conditions under which they are procured. This reality forces essentially every legitimate health monitoring application to employ some form of statistical significance test against data from the undamaged condition, gathered under a wide range of operational and environmental conditions. In the case of a RINAS-based system, this range of operational and environmental conditions will be limited. As shown in Su and Kijewski-Correa (2007a), a Gaussian model can generally be applied conservatively to represent the DSF values associated with the reference pool; damage is indicated with P-percent certainty whenever a DSF value falls outside of this confidence interval.

As discussed in the previous section, DSFs have been proposed in conjunction with a variety of underlying regressive-type models. Sohn, *et al.*'s (2000) two-stage AR-ARX approach utilized the statistics of the residual errors as its DSF, while others like Nair, *et al*. (2006) have used an ARMA time series representation for the k^{th} measured acceleration response, retaining only the first three AR coefficients as direct damage indicators:

$$DSF1s_k = \frac{\alpha_{k1}}{\sqrt{\alpha_{k1}^2 + \alpha_{k2}^2 + \alpha_{k3}^2}} \tag{3}$$

Note that such coefficient-based DSFs are attractive for use in WSNs since only the coefficients themselves need to be retained and analyzed for detection. Eq. (3) will be termed the *static* homogeneous damage sensitive feature or *DSF1s*, in that the coefficients to be monitored are specified *a priori*. However, as alternate underlying models, e.g., AR, may be considered to further reduce computational burdens in WSNs, or as heterogeneous detection frameworks using BAR models are explored, the first coefficient may not always be the most sensitive to damage. In fact, in Kijewski-Correa, *et al.* (2006b), it is demonstrated that in some applications, the first AR coefficient does not show statistically significant sensitivity to damage. As a result, a new DSF has been proposed that is more adaptive to changes in the sensitivity of AR coefficients given the variations in loading condition, damage location and severity (Kijewski-Correa, *et al*. 2006b).

The premise for this DSF is slightly different than its predecessors in that it directly incorporates information from the reference pool of undamaged states. This adaptive or *data-driven DSF* for the k^{th} recorded response is defined as the AR coefficient that has changed most significantly when compared to the average values stored in the reference database:

$$DSF1d_k = \max\left[\left.\frac{|\alpha_{ik} - \underset{ref}{avg}[\alpha_{ki}]|}{\underset{ref}{std}[\alpha_{ki}]}\right|_{i=1:na}\right] \tag{4}$$

Here the notation *ref* refers to the mean (*avg*) and standard deviation (*std*) of the AR coefficients in the reference database. Eq. (4) will be called *DSF1d*, since it is a dynamic, homogeneous representation.

Similarly, *DSF1d* is can be modified for a heterogeneous representation to better exploit the most sensitive bivariate AR coefficients:

$$DSF2d_k = \max\left[\left.\frac{|\alpha_{ik} - \underset{ref}{avg}[\alpha_{ik}]|}{\underset{ref}{std}[\alpha_{ik}]}\right|_{i=1:Na}, \left.\frac{|\beta_{jk} - \underset{ref}{avg}[\beta_{jk}]|}{\underset{ref}{std}[\beta_{jk}]}\right|_{i=0:Nb}\right] \tag{5}$$

Eq. (5) is termed a *Bivariate Regressive Adaptive Index (BRAIN)* for damage detection within a decentralized, wireless sensor network, where the notation *ref* again indicates that these statistics are calculated respectively over all the acceleration (α) and strain (β) AR coefficients in the reference pool.

Two key features should be noted regarding Eqs. (4) and (5). First, the original AR coefficients for each vibration signal in the reference database need not be stored locally at the sensor node; only the mean and standard deviation of each coefficient are required. This dramatically reduces not only the required on-board memory, but also any computation (and power drain) associated with the manipulation of a reference database. Second, 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 only with a specific model type or sensor in mind. This also implies that if there is a location where higher order coefficients are more sensitive to damage, they will be exploited. Thus the DSF is truly data-driven.

5. Verification

A number of established benchmarks, community data sets, and simulated data sets will be used to validate the concepts introduced herein. The validation in this section will be concerned with two major hypotheses:

(1) Data-driven DSFs are more robust and reliable than their static counterparts, even in homogeneous sensor networks.

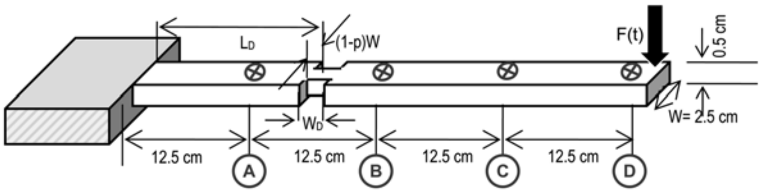


Fig. 3 Rendering of simulated thin cantilever beam model (not to scale)

(2) Heterogeneous sensing enhances the detection capability of data-driven DSFs.

Before presenting results supporting these hypotheses, a brief summary of the benchmarks is provided, each driven by a white noise excitation. First is Los Alamos National Laboratory's (LANL) vibrating disc system, formed by eight translating masses interconnected by springs and driven by an electro-dynamic shaker (Sohn and Farrar 2001). Damage scenarios were simulated by changing the properties of the springs: in this case the spring between masses 5 and 6 is replaced with one having a 14% smaller spring constant. The acceleration responses of the masses are used herein to validate Hypothesis 1. This hypothesis is also validated by the 12 degree-of-freedom (12DOF) lumped mass model of the Phase I IASC-ASCE Structural Health Monitoring Benchmark structure (shown later in Fig. 6), whose details can be found in Johnson, *et al*. (2004). Unfortunately, these and other benchmarks and datasets available in the literature do not include strain data. As a result, a data set was generated for the validation of the heterogeneous damage assessment framework using a finite element model of a thin cantilever beam as shown in Fig. 3, with Gaussian white noise input at the free end. Acceleration and surface strain time history pairs are repeatedly simulated at the four locations shown in Fig. 3. For the cases considered in this study, damage will be subsequently introduced to the beam through a transverse cut, symmetrically imparted midway between points A and B. The transverse dimension of the cut is specified as a percentage (for example p=20%) of the total width of the beam; the longitudinal dimension of the cut is fixed at 5% of the total length of the beam for this study (W_D=0.05 L=2.5 cm), as also shown in Fig. 3. This benchmark will be used to validate the second hypothesis.

5.1. Hypothesis 1: data-driven DSFs are more robust and reliable

In order to affirm the benefits of a data-driven DSF, all other variables in the damage detection problem must be isolated. As a result, only homogeneous (acceleration) data will be considered and the underlying model (AR) used for data reduction will be kept consistent. Note that *DSF1s* was intended for use with ARMA models (Nair, *et al*. 2006). The use of *DSF1s* with a pure AR model is not intended to purposefully discredit this DSF, but rather to demonstrate the advantages of a data-driven DSF when the underlying model is changed.

This hypothesis will first be vetted using the LANL vibrating disk dataset. A 97.5% level of confidence is adopted with a reference pool consisting of 8 independent trials for the undamaged system. Each time a DSF value falls outside of this confidence interval, damage is detected and is signified in Table 1 in bold along with the damage detection rate (Det. Rate) calculated over four experimental trials. Two major observations can be drawn from these results. First, the dynamic DSF (*DSF1d*) is more successful in detecting damage: 100% detection rate at all locations vs. 53% average detection rate for the static DSF (*DSF1s*). Second, both DSFs showed a certain capability to locate damage, with the largest values of *DSF1d* being near the damage position.

Table 1 Damage detection results for static and dynamic homogeneous damage sensitive features using LANL vibrating mass dataset

	Mass 1		Mass 2		Mass 3		Mass 4	
	DSF1s	*DSF1d*	*DSF1s*	*DSF1d*	*DSF1s*	*DSF1d*	*DSF1s*	*DSF1d*
Test 1	-0.214	**5.983**	0.482	**3.881**	0.516	**3.246**	**0.590**	**13.743**
Test 2	-0.215	**6.371**	0.473	**5.384**	**0.473**	**5.076**	**0.575**	**15.837**
Test 3	-0.193	**8.278**	0.484	**3.835**	0.506	**4.832**	0.530	**6.548**
Test 4	-0.236	**8.039**	0.486	**4.926**	0.510	**1.839**	0.546	**7.643**
Det. Rate	**0%**	**100%**	**0%**	**100%**	**25%**	**100%**	**50%**	**100%**
	Mass 5		**Mass 6**		**Mass 7**		**Mass 8**	
	DSF1s	*DSF1d*	*DSF1s*	*DSF1d*	*DSF1s*	*DSF1d*	*DSF1s*	*DSF1d*
Test 1	**0.531**	**19.042**	**0.624**	**4.668**	**0.540**	**7.394**	**0.604**	**6.240**
Test 2	0.573	**13.179**	**0.628**	**4.086**	0.548	**5.161**	**0.643**	**5.135**
Test 3	**0.617**	**6.908**	**0.688**	**12.482**	**0.516**	**9.015**	**0.773**	**8.612**
Test 4	**0.631**	**9.890**	**0.695**	**14.155**	**0.539**	**8.781**	**0.771**	**8.745**
Det. Rate	**75%**	**100%**	**100%**	**100%**	**75%**	**100%**	**100%**	**100%**

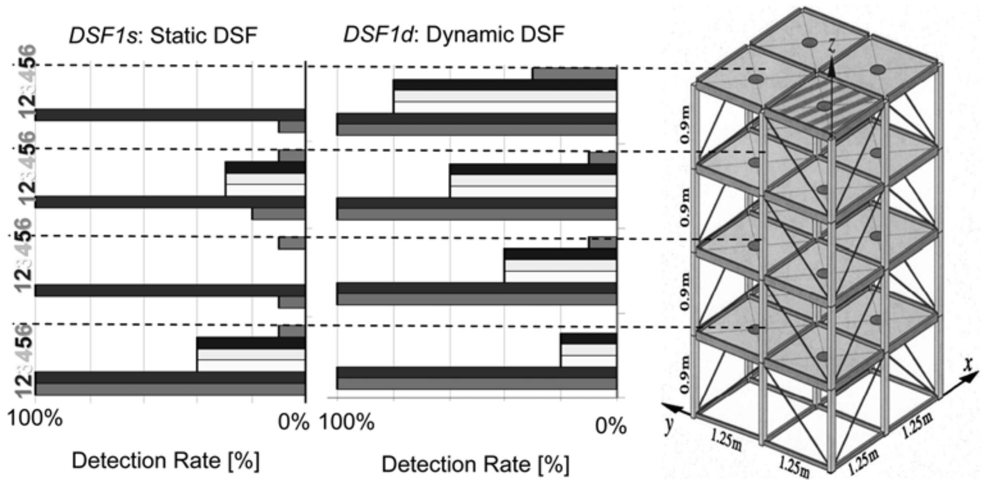


Fig. 4 Detection rates for homogeneous static and dynamic damage sensitive features: Phase I IASC-ASCE Benchmark

To further explore the sensitivity of static and dynamic DSFs to damage severity, the IASC-ASCE Benchmark structure is now considered, testing each damage pattern over 10 independent trails and a reference pool of 50 independent simulations of the undamaged case using a 97.5% confidence interval. While the damage detection rates at all floors are provided in Fig. 4, specific examples of *DSF1s* and *DSF1d* values for DP 0-3 can be found in Su and Kijewski-Correa (2007b). Note that the DP0 damage case, where no damage is actually imparted, is provided to evaluate any tendency toward false positives and should ideally have a 0% detection rate.

Several important conclusions can be drawn regarding overall damage detection capability, i.e. ability to detect damage from any sensor output:

(1) Neither DSF appears susceptible to false positives.

(2) For the most severe level of damage (DP2), both *DSF1s* and *DSF1d* can detect damage consistently based on the response at any of the floors. For the other severe damage case (DP1), *DSF1s* has an average detection rate of 35%, while *DSF1d* has a consistent detection rate of 100%.

(3) For the moderate and minor damage cases (DP3-6), *DSF1s* is not as successful with an average detection rate of 17.5% for modest damage levels (DP3-5) and 7.5% for minor damage levels (DP6). Detection capability is strongest at floors 1 and 3, where damage has been imposed. This indicates that when the damage severity is minor to modest, this static DSF is best suited for detection near the point of damage, implying the need for high sensor density. Meanwhile, *DSF1d* results in average detection rates of 50% under moderate damage (DP3-5) and 12.5% under minor damage (DP6). Since the acceleration response increases up the building, the findings here also indicate that the homogeneous data-driven DSF performs better as the response amplitude increases, consistent with the findings of Su and Kijewski-Correa (2007a). This makes this class of DSF well-suited for applications where dense sensor networks are not feasible and measurements may only be taken at limited locations.

(4) The *DSF1d* values have been shown to increase with the damage level (Su and Kijewski-Correa 2007b), providing a means to directly quantify severity of damage.

These overall damage detection results are also consistent with the previous findings of Su and Kijewski-Correa (2007a), which compared the performance of Eqs. (3) and (4) for the thin cantilever beam under minor levels of damage. These results are summarized in Table 3, which will be revisited in a subsequent example. However, while the capability to signify the presence of damage and even relative severity is attractive, the ability to localize damage is also necessary. To assist in this, a damage quantification index (DQI) is introduced:

$$DQI = \frac{\left|\phi_{un}{}^{T}\phi\right|^{2}}{\phi_{un}{}^{T}\phi_{un}\phi^{T}\phi} \tag{6}$$

where ϕ is the vector of AR coefficients associated with the state being evaluated $\phi = [\alpha_1, \alpha_2, \ldots \alpha_{na}]$ and ϕ_{un} is the vector of AR coefficients associated with the undamaged state $\phi_{un} = [\alpha_1, \alpha_2, \ldots \alpha_{na}]_{un}$, for a given measurement location. For undamaged states, the two vectors should be correlated and DQI should approach unity. As damage levels progressively increase, the correlation should reduce and DQI should tend toward zero. Again, statistical significance can be verified by comparing the DQI to the confidence interval derived from the undamaged reference pool. The DQI was applied to the IASC-ASCE Benchmark Problem for DP1-2, with the results presented in Table 2. Note that the localization of damage for both these damage patterns is successfully achieved. Still, these results do not consider the added flexibility of a data-driven DSF to incorporate multiple sensor types. The advantages of this capability are now explored.

5.2. Hypothesis 2: heterogeneous sensing enhances detection capability

Thus far, the utility of a data-driven DSF has been demonstrated for homogeneous representations (acceleration only). To demonstrate the superior performance of *DSF2d* in Eq. (5), damage detection results are compared between it and its homogeneous counterpart, *DSF1d* in Eq. (4), using the thin beam model. Again the data reduction will be accomplished using AR and BAR models, and transverse cuts will be p = 0, 10 and 30% of the beam width. The cut will be introduced at L_D = 18.75 cm, midway between points A and B. Confidence limits at 97.5% are again employed, based on a reference pool

Table 2 Summary of detection results for thin cantilever beam: comparison of static homogeneous and homogeneous/heterogeneous dynamic damage sensitive features

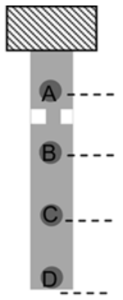
		Static DSF			Dynamic DSF					
		Homogeneous			Homogeneous			Heterogeneous		
		DSF1s			*DSF1d*			*DSF2d*		
	Volume Lost	0%	0.5%	1.5%	0%	0.5%	1.5%	0%	0.5%	1.5%
	Det. Rate	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**10%**	**100%**	**100%**
	Avg. DSF	-0.38	-0.38	-0.38	0.82	0.82	0.86	1.01	32.52	136.9
	Det. Rate	**0%**	**0%**	**20%**	**0%**	**60%**	**60%**	**0%**	**100%**	**100%**
	Avg. DSF	-0.84	-0.79	-0.61	1.02	1.47	1.75	0.84	2.96	4.90
	Det. Rate	**0%**	**0%**	**20%**	**0%**	**20%**	**100%**	**0%**	**0%**	**100%**
	Avg. DSF	0.73	0.68	0.48	0.95	1.35	2.15	0.83	1.01	1.87
	Det. Rate	**0%**	**0%**	**0%**	**0%**	**0%**	**50%**	**0%**	**10%**	**90%**
	Avg. DSF	-0.42	-0.28	-0.37	0.92	1.07	1.53	0.84	1.19	2.14

Table 3 Damage quantification index results for first two damage patterns of IASC-ASCE Benchmark Problem

	Floor 1		Floor 2		Floor 3		Floor 4	
Data Pool	Mean	0.992	Mean	0.989	Mean	0.988	Mean	0.974
	Std.	0.007	Std.	0.012	Std.	0.011	Std.	0.019
	Threshold	0.978	Threshold	0.965	Threshold	0.968	Threshold	0.937
DP 1	DQI	**0.867**	DQI	0.978	DQI	0.984	DQI	0.981
	Damage Location?	**Yes**	Damage Location?	No	Damage Location?	No	Damage Location?	No
DP 2	DQI	**0.607**	DQI	**0.643**	DQI	**0.623**	DQI	**0.797**
	Damage Location?	**Yes**	Damage Location?	**Yes**	Damage Location?	**Yes**	Damage Location?	**Yes**

comprised of 100 independent random simulations of the undamaged beam, and the percentage of volume lost due to damage is specified for each case to demonstrate the minor level of damage being considered. The 0% damage case is again offered to evaluate any tendency toward false positives. Table 3 summarizes the detection rate and average DSF values over the 10 independent trials, while the complete table of DSF values can be found in Su and Kijewski-Correa (2007a). Note in Table 3 that the each pair of rows indicates the detection rate (Det. Rate) and average (Avg.) DSF at a specific location on the cantilever beam, as indicated by the position of the rows with respect to the inset schematic. From these results, several important conclusions can be drawn about the heterogeneous formulation:

(1) Incidence of false positives for the heterogeneous approach (*DSF2d*) is negligible in comparison with its detection rate.

(2) The larger of the two damage scenarios can be identified reliably at all measurement locations for the heterogeneous approach (*DSF2d*). The vast improvement in detection capability in the vicinity of damage can be largely credited to the heterogeneous framework that recognizes the fact that structural response cannot be characterized by acceleration alone and a DSF must adapt to the response component most critical at that location.

(3) Consistent with the homogeneous scheme, the heterogeneous DSF's (*DSF2d*) detection rate falls off further from the damage location for the smaller of the two damage scenarios.

(4) Like their homogeneous counterparts, the heterogeneous DSF (*DSF2d*) values increase with the damage level and proximity to the damage location (Su and Kijewski-Correa 2007a).

Thus, damage detection capability within the heterogeneous framework is dramatically improved in comparison to homogeneous methods, without a sizeable increase in the rate of false positives, even for the very modest levels of damage considered here.

6. Conclusions

The dire condition of Civil Infrastructure in the United States requires a commitment on the part of both municipalities and the engineering community to develop more effective and efficient means to proactively identify damage in its early stages to preserve life safety and minimize economic impacts to society. With the recent advances in hardware, wireless sensor networks are becoming an increasingly viable option to achieve the level of ubiquitous sensing necessary to monitor these expansive infrastructure systems. This study focused on the concept of a multi-scale wireless sensor network for operational health monitoring of civil infrastructure systems by first over viewing the general network philosophy and attributes in the areas of data acquisition, data reduction, assessment and decision making. The data acquisition aspect included a scalable wireless sensor network acquiring acceleration and strain data, for a heterogeneous sensor array. This WSN is triggered using a Restricted Input Network Activation Scheme (RINAS) to extend network lifetime and reduce the size of the requisite undamaged reference pool. Major emphasis was given in this study to data reduction and assessment aspects that enabled a decentralized approach operating within the hardware and power constraints of wireless sensor networks to avoid issues associated with packet loss, synchronization and latency. After over viewing various models for data reduction in WSNs, the concept of a data-driven Bivariate Regressive Adaptive INdex (BRAIN) for damage detection was presented. Its novel feature is a data-driven DSF operating on heterogeneous sensor data with minimal computational and local data storage requirements, all couched within a probabilistic framework to accommodate operational and environmental variability. Subsequent examples using experimental and simulated data verified two major hypotheses related to the BRAIN concept: (i) data-driven damage metrics are more robust and reliable than their static counterparts, even when homogeneous sensing is used, and (ii) the use of heterogeneous sensing enhances overall detection capability of such data-driven damage metrics, without significant increase in false positives. Capabilities for localization and quantification of damage severity were also noted. These findings speak not only to the flexibility offered by a data-driven DSF and its ability to operate within a decentralized system identification framework, but also the enhanced sensitivity to damage facilitated by a heterogeneous approach to detection.

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References

Hill, J., Szewczyk, R., Woo, A., Hollar, S., Culler, D. and Pister, K. (2000), "System architecture directions for networked sensors", *Proc. of Int. Conf. on Architectural Support for Programming Languages and Operating Systems (ASPLOS)*, November.

Johnson, E.A., Lam, H.F., Katafygiotis, L.S. and Beck, J.L. (2004), "Phase I IASC-ASCE structural health monitoring benchmark using simulated data", *J. Eng. Mech*., **130**(1), 3-15.

Kijewski-Correa, T., Haenggi, M. and Antsaklis, P. (2006a), "Wireless sensor networks for structural health monitoring: a multi-scale approach", *Proc. of 2006 ASCE Structures Congress, 17th Analysis & Computation Specialty Conf.*, St. Louis, May.

Kijewski-Correa, T., Su, S., Abittan, E. and Antsaklis, P.J. (2006b), "On the use of heterogeneous, wireless sensor networks for damage assessment in bridges under unknown excitations", *Proc. of 4th World Conf. on Structural Control and Monitoring*, San Diego, July.

Kottapalli, V.A., Kiremidjian, A.S., Lynch, J.P., Carryer, E., Kenny, T.W., Law, K.H. and Lei, Y. (2003), "Two-tiered wireless sensor network architecture for structural health monitoring", *Proc. of SPIE - The Int. Society for Optical Engineering,* **5057**, 8-19.

Law, S.S., Li, X.Y., Zhu, X.Q. and Chan, S.L. (2005), "Structural damage detection from wavelet packet sensitivity", *Eng. Struct.,* **27**(9), 1339-1348.

Lynch, J.P., Sundararajan, A., Law, K.H., Kiremidjian, A.S. and Carryer, E. (2004), "Embedding damage detection algorithms in a wireless sensing unit for operational power efficiency", *Smart Mater. Struct.,* **13**, 800-810.

Mitchell, K., Rao, V.S. and Pottinger, H.J. (2002), "Lessons learned about wireless technologies for data acquisition", *Proc. of SPIE Smart Structures and Materials 2002: Smart Electronics, MEMS, and Nanotechnology*, San Diego, March, **4700**, 331-341.

Nair, K.K., Kiremidjian, A.S. and Law, K.H. (2006), "Time series-based damage detection and localization algorithm with application to the ASCE benchmark structure", *J. Sound Vib.,* **291**(3), 349-368.

Sohn, H., Farrar, C.R., Hunter, N.F. and Worden, K. (2000), "Structural health monitoring using statistical pattern recognition techniques", *J. Struct. Eng*., **126**(11), 1356-1363.

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

Straser, E.G. and Kiremidjian, A.S. (1998), *Report No. 128: Modular, Wireless Damage Monitoring System for Structures*, John A. Blume Earthquake Engineering Center, Department of Civil and Environmental Engineering, Stanford University.

Su, S. and Kijewski-Correa, T. (2007a), "Performance verification of bivariate regressive adaptive index for structural health monitoring", *Proc. of SPIE Smart Structures and Materials & Nondestructive Evaluation and Health Monitoring*, San Diego, March.

Su, S. and Kijewski-Correa, T. (2007b), "On the use of a bivariate regressive adaptive index for structural health monitoring", *Proc. of Structural Health Monitoring and Intelligent Infrastructure (SHM-II) 2007*, Vancouver, November.

Wang, Y., Lynch, J.P. and Law, K.H. (2005), "A wireless structural health monitoring system with multithreaded sensing devices: design and validation", *Struct. Infrastruct. E.*, **3**(2), 103-120.