Performance Verification of Bivariate Regressive Adaptive Index for Structural Health Monitoring

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ABSTRACT

This study focuses on data-driven methods for structural health monitoring and introduces a Bivariate Regressive Adaptive INdex (BRAIN) for damage detection in a decentralized, wireless sensor network. BRAIN utilizes a dynamic damage sensitive feature (DSF) that automatically adapts to the data set, extracting the most damage sensitive model features, which vary with location, damage severity, loading condition and model type. This data-driven feature is key to providing the most flexible damage sensitive feature incorporating all available data for a given application to enhance reliability by including heterogeneous sensor arrays. This study will first evaluate several regressive-type models used for time-series damage detection, including common homogeneous formats and newly proposed heterogeneous descriptors and then demonstrate the performance of the newly proposed dynamic DSF against a comparable static DSF. Performance will be validated by documenting their damage success rates on repeated simulations of randomly-excited thin beams with minor levels of damage. It will be shown that BRAIN dramatically increases the detection capabilities over static, homogeneous damage detection frameworks.

Keywords: Structural Health Monitoring, Damage Detection, Wireless Sensor Networks

1. INTRODUCTION

Structural health monitoring (SHM) has been attracting much attention in a civil engineering community charged with the maintenance of a vast diverse, aging Civil Infrastructure, given the inefficiency of manual inspection and rating. SHM's objective is to detect, locate, and assess the severity of any structural damage due to service loads, as well as extreme events, generally by analyzing vibrational data. In order to offset economic expense and public inconvenience, damage should be detected in its early stages to enable less intrusive, proactive maintenance. While there are a number of approaches to this problem, the authors have specifically focused on wireless sensor networks (WSN) recording ambient vibrations, due its ease of installation and minimal intrusion on operations. In particular, those networks that utilize the local processing capability at the sensor node can minimize the communication and thereby power demands on the network, thus extending its lifetime. A summary of the authors' approach to these issues is summarized in Fig. 1[1]. Given the infancy of these efforts, the reliability of damage detection in WSNs, in light of the limited on-board computational and sensing capabilities and the presence of model, load and environmental variabilities, is an important issue to be addressed.

The approach advocated herein builds on statistical signal processing techniques in the time domain to minimize the impact of these variabilities. This approach has been used in a number of applications, though each using different auto-regressive models to reconstruct largely acceleration responses and extract features sensitive to damage. These efforts have demonstrated their potential to provide effective and automated damage diagnosis for wireless sensor networks[1-4], [6-9]. Unfortunately, the performance of these techniques and the damage sensitive features (DSF) they employ are entirely reliant on the underlying model used to represent the time series -- auto-regressive models with exogenous inputs (AR-ARX) and auto-regressive moving averages models (AR-ARMA) being but two examples. Unfortunately, the model orders required for such autoregressive representations can strain the limited computational capability of the local processors. Due to similar constraints, the DSFs employed 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. Therefore, it is useful to pose two questions: 1) Can trade-offs between model order and detection capability within such computationally constrained frameworks be facilitated by diversifying the response information considered through a form of heterogeneous detection? And 2) can a simple yet adaptive DSF be developed that can accommodate various underlying models and even significant changes in the application, while still providing reliable detection?

These questions will be pursued in the following study by first evaluating several regressive-type models, including the formats commonly used in homogeneous sensing and those newly proposed for heterogeneous detection (Fig. 1) to demonstrate their performance. Then a more robust, data-driven DSF will be introduced that automatically adapts to the data set, extracting the most damage-sensitive model features, which vary with location, damage severity, and loading condition. The performance of this data-driven DSF in comparison with a similar "static" DSF will be presented. It will be shown that this data-driven feature is key to providing the most robust damage sensitive feature incorporating all available sensing types for a given application. Finally it will be demonstrated that by combining the capability for heterogenous sensing and the data-driven DSF concept, through what will be termed a Bivariate Regressive Adaptive INdex (BRAIN), detection capability is dramatically enhanced. In all cases, proof-of-concept is provided through repeated simulation documenting detection success rates on randomly-excited thin beams with minor levels of damage. However, before evaluating the performance of the underlying time-series models or the utility of a data-driven DSF, the details of the beam finite element models (FEM) used for proof-of-concept are first presented.

FEATURE	SELECTION	ADVANTAGE
Sensors	Acceleration, Strain	More sensitive to damage when combined
Excitation	Ambient, Event Triggering	No disruption of operation, maximize lifetime
Network Architecture	Two-tiered, wireless globally, wired locally	Low power, low latency, scalable
Damage Detection	Decentralized, low order, time-series, local fusion	Easily embedded, event synchronized, more reliable
Variability (Operational, Environmental)	Statistical Significance, Restrict Network Activation	Reduce false positives, reduce reference pool size
Power Consumption	Decentralized identification, event triggering, exploit sub-networks	Maximize battery life

Fig. 1. Overview of key features of proposed SHM framework.[1]

2. DESCRIPTION OF CANTILEVER BEAM MODEL

Throughout this study, simulation results will be used to demonstrate performance. The simulation will employ an FEM of a cantilever beam of the form shown in Fig. 2, with Gaussian white noise input at the free end. In the context of civil structures, this would be analogous to a randomly-excited, slender tall building. The beam is modeled using a series of finite elements interconnected only at the nodes. Each node will be assumed to have only two degrees-of-freedom: a transverse displacement and rotation. Acceleration and surface strain time history pairs are repeatedly simulated at the four locations shown in Fig. 2.

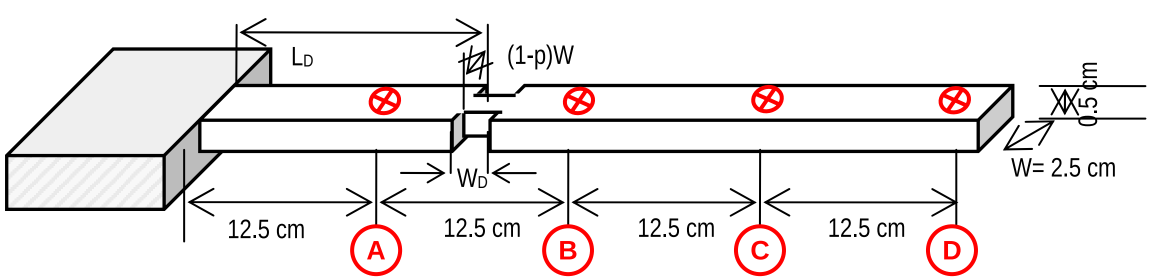


Fig. 2. Rendering of simulated beam model (not to scale).

A collection of simulated strain/acceleration pairs from the undamaged beam form the reference database that will be used in subsequent statistical significance tests. 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 = 0.05L = 2.5 cm), as shown in Fig. 2. Acceleration and strain signal pairs are repeatedly simulated at points A-D for various percent-damage scenarios.

3. TIME-SERIES MODELS

As discussed previously, the time-series damage detection problem is completely reliant on the underlying model used to represent the time series. Therefore, this section now explores the significance of this model choice, first for more accurate representations of the signal, and then for damage detection. Note that in general, measured signals are standardized before a model is fit by demeaning and then normalizing by their standard deviation. It is assumed this action is performed on all measured signals before they are fit as part of the reference database or DSF evaluation.

3.1 Homogeneous Representations

Two types of regressive models had been used previously for the time-series characterization of vibration signals. The most basic is the AR model, where the k^{th} acquired vibration signal is represented at each time step n by na AR terms[5]:

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

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. Similarly, an ARMA formulation can be used [5]:

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

where β_{kj} is the j^{th} MA coefficient. This approach has been used by Nair et al.[7]. In either case, the resulting AR coefficients α_{ki} or the residual error ζ_k can be retained for damage detection. A related two-stage AR-ARX approach by Sohn et al.[9] uses the residual error of an AR representation ($\zeta_{k,AR}$) as the exogenous input to a second stage $na+nb$ order ARX model:

$$\tilde{A}_k(n) = \sum_{i=1}^{na} \alpha_{ki} A(n-i) + \sum_{j=0}^{nb} \beta_{kj} \zeta_{k,AR}(n-j) + \zeta_k(n) \tag{3}$$

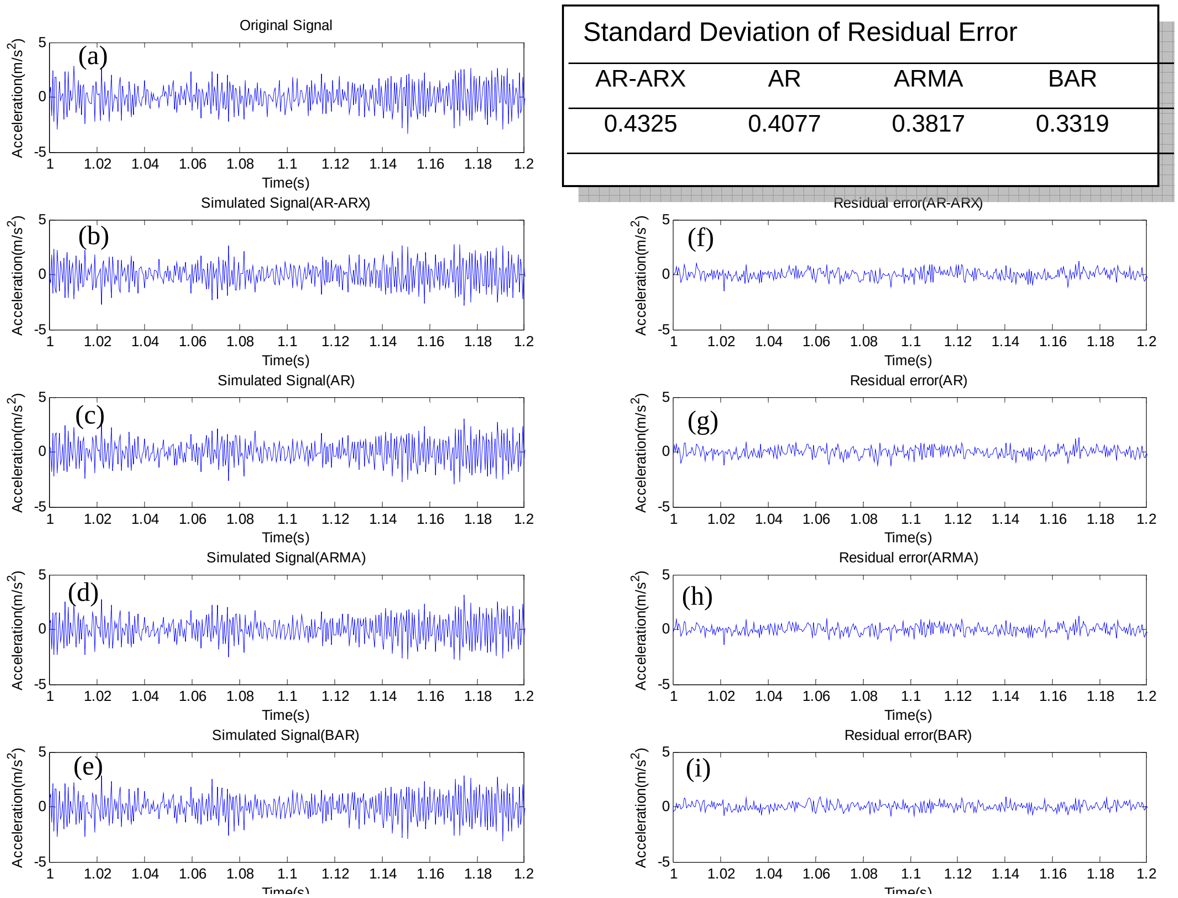
where α_{ki} and β_{kj} are the i^{th} and j^{th} coefficients in the expansion and ζ_k is the residual error, who statistics are utilized for detection of damage.

3.2 Heterogeneous Representations

Kijewski-Correa et al.[2] later introduced an alternate formulation based upon multiple vibration signals from different sensing elements, e.g., acceleration A and strain S, realizing the unique information regarding damage that can be carried by each. Various formulations that model the interrelation between these two measured quantities have been offered[1], though the present study specifically focuses on the *bivariate autoregressive (BAR) model* between strain and acceleration. In this representation, the k^{th} standardized strain and acceleration data pair *(A, S)* is fit by a $na+nb$ order model:

$$\tilde{A}_k(n) = \sum_{i=1}^{na} \alpha_{ki} A(n-i) + \sum_{j=0}^{nb} \beta_{kj} S(n-j) + \varsigma_k(n) \tag{4}$$

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.



Standard Deviation of Residual Error

AR-ARX	AR	ARMA	BAR
0.4325	0.4077	0.3817	0.3319

Fig. 3. Representation of (a) acceleration signal by (b) AR-ARX, (c) AR, (d) ARMA, and (e)BAR, with residual errors by (f) AR-ARX, (g) AR, (h)ARMA, and (i) BAR.

3.3 Performance Assessment

Before assessing the ability to detect damage, it is first useful to note the accuracy with which these various representations model a given acceleration signal. Fig. 3 shows an example of an acceleration signal from an undamaged beam that is fit with 20th order models: AR (*na=20*), ARMA (*na=13; nb=7*), ARX (*na=13; nb=7*) and BAR (*na=13; nb=7*). The reconstructions by each model are also provided in Fig. 3, along with the residual errors and an inset summary of their statistics. The results in Fig. 3 underscore the superior performance of the BAR representation for same effective model order. Note however that the true strengths of the two-stage approach employing AR-ARX models cannot be underscored here since environmental and operational variability is not simulated.

3.4 Computational Burden

While one of the primary merits of Sohn et al.'s[9] AR-ARX approach is this resistance to changes in the environmental and operational conditions of the system, as noted by Lynch et al.[6], 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. Kijewski-Correa et al.[2] later introduced an alternate approach, which minimizes environmental and operational conditions through a restricted input network activation scheme (RINAS), permitting the use of a one-stage autoregressive model, without the need for signal reconstruction and residual error calculation. Thus, it is now useful to examine whether this simplified autoregressive model possesses sufficient sensitivity to minor levels of damage.

4. DAMAGE SENSITIVE FEATURES

In many practical detection and 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 damage detection into a probabilistic context capable of distinguishing these benign variabilities from more serious indicators of damage. Sohn et al.'s[9] two-stage AR-ARX approach utilized the statistics of the residual errors as its DSF, while others like Nair et al.[7] have used an ARMA time series representation, retaining only the AR coefficient's themselves as direct damage indicators. Such coefficient-based DSFs are attractive for use in WSNs in that only the AR coefficients themselves need to be retained and analyzed for detection, reducing the computational/memory burdens associated with signal reconstruction and error estimation. This class of DSF will now be explored in more detail.

4.1 DSFs for Homogeneous Representations

Through extensive investigation, Nair et al.[7] found that the first AR coefficient of an ARMA representation was the most sensitive to damage within their homogeneous detection framework. 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 AR coefficient may not be the most sensitive to damage in some cases. As a result, a new DSF has been proposed that is more adaptive to changes in the sensitivity of AR coefficients[1]. The premise for this DSF is slightly different in that it directly incorporates information from the reference pool of undamaged states. Such reference pools are used by all damage detection methods in this class and are populated by acquiring multiple vibration signals under varying operational and environmental conditions from the structure in its undamaged or initial state. This reference pool may include strain and/or acceleration data (or any other desired response time history). Each of these reference signals should be standardized and then fit by the desired model (AR, ARMA, BAR, etc.), with the AR coefficients stored in the reference database. This adaptive or *data-driven DSF* is first defined as the AR coefficient that has changed most significantly when compared to the average values stored in the reference database:

$$DSF_k = \max\left[\left. \frac{\left| \alpha_{ki} - \underset{ref}{avg}[\alpha_{ki}] \right|}{\underset{ref}{std}[\alpha_{ki}]} \right|_{i=1:na} \right] \tag{5}$$

Two key features should be noted:

1) The original AR coefficients for each vibration signal in the reference database need not be stored locally; only the mean and standard deviation of each coefficient are required. Thus only *2na* reference values are finally stored at each sensor node after some training period for the WSN. Again keep in mind that *na* is relatively small (< 20). 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.

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. 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 data-driven, and again involves minimal computational effort.

Statistical significance must still be established and can be done so during the training period by evaluating the DSF in equation (5) for each reference signal against the remaining reference signals in the pool. As demonstrated by Fig. 4 a Gaussian model can generally be applied to represent the DSF values associated with the reference pool, allowing the user to specify a desired percentile of statistical significance, e.g., 95%. Therefore, let DSF_P represent the DSF from the reference pool at percentile *P*. Then damage is indicated with P-percent certainty whenever a future DSF value satisfies the following inequality: $DSF_k > DSF_P$. For the discussions which follow, the damage pool will be comprised of 100 independent random simulations of the undamaged beam described in Section 2. Only acceleration data will be considered in this section and both the acceleration and strain data will be employed in Section 4.2.

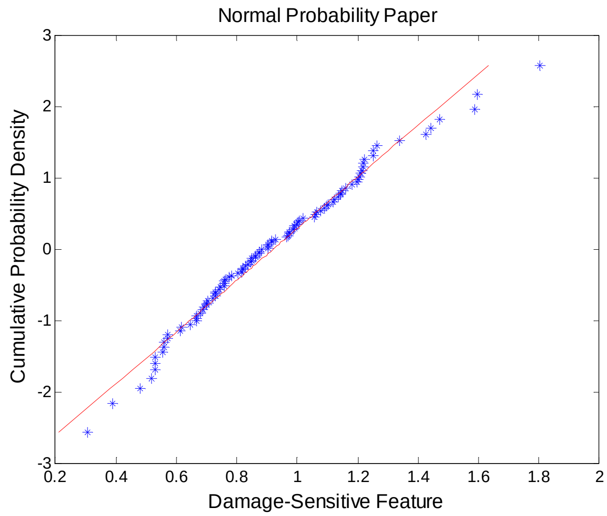


Fig. 4. Plot of distribution of homogeneous data-driven DSF for refrence pool of undamaged states, using normal probability paper.

To verify the performance of the data-driven homogeneous DSF in equation (5), it is now compared to a "static" DSF also based on AR coefficients[7]:

$$DSF_k = \frac{\alpha_{k1}}{\sqrt{\alpha_{k1}^2 + \alpha_{k2}^2 + \alpha_{k3}^2}} \tag{6}$$

For consistency, the same AR model is used to represent the acceleration data and only the DSFs applied are varied. (It should be noted that an ARMA model was used by Nair et al.[7] and not the AR model (Eq. 1) applied here.) Various degrees of damage (p = 0, 10, 30%) are explored for cuts introduced at L_D = 18.75 cm, midway between points A and B (see Fig. 2). Each damaged simulation is run 10 times to explore the repeatability of the results. A *P=97.5%* one-sided confidence interval is specified for distinguishing statistically significant damage in equation (5), while a two-sided confidence interval at 97.5% is used with equation (6). The results for both the static and data-driven DSFs are provided in Table 1, where bold-faced values indicate that $DSF_k > DSF_P$ and thus damage is detected. The total cross sectional area lost due to damage ($W_D p/L$) is specified for each damage case to demonstrate the minor level of damage being considered and performance will be quantified by the damage detection rate (Det Rate). Note the 0% damage case is provided to evaluate any tendency toward false positive detection.

Several important conclusions can be drawn from Table 1:

1. Neither DSF appears susceptible to false positives.
2. For the two cases of actual damage, the static DSF (Eq. 6) is generally unsuccessful. Only a 20% detection rate is recorded in one instance, at Point C and only for the larger of the two damage cases.
3. The dynamic DSF (Eq. 5) has no success detecting damage at point A, which is not surprising since this point is closest to the fixed end, thus producing the smallest of the simulated acceleration responses.
4. For the smallest level of damage, the dynamic DSF (Eq. 5) has its highest detection rate at point B, which is logical since damage is near this node. Beyond point B, the smaller of the two damage scenarios is scarcely detected.
5. For the larger of the two damage cases, the dynamic DSF (Eq. 5) has reasonable success at points B (60%), C (100%) and D (50%). The good performance at location C is due to it being ideally situated at a location where acceleration responses are larger, without being too far from the damage location.

6. The results also indicate that the data-driven DSF (Eq. 5) values and the detection rate both increase with damage level, so the method will not only be more reliable as damage increases beyond these modest levels, but the correlation of the DSF to damage level provides a means to quantify the extent of damage.

These findings clearly demonstrate the power of a data-driven DSF, even when only acceleration responses are considered.

Table 1. Damage detection results for Static (Eq. 6) and Data-Driven (Eq. 5) DSF

	POINT A						POINT B					
	Static DSF			Data-Driven DSF			Static DSF			Data-Driven DSF		
Threshold	$DSF_{97.5\%}$ = (-0.49, -0.3)			$DSF_{97.5\%}$=1.54			$DSF_{97.5\%}$ = (-1.17, -0.42)			$DSF_{97.5\%}$ =1.49		
Area Lost	0%	0.5%	1.5%	0%	0.5%	1.5%	0%	0.5%	1.5%	0%	0.5%	1.5%
Test 1	-0.42	-0.41	-0.39	1.01	1.04	1.06	-0.94	-0.97	-0.65	0.99	1.04	1.38
Test 2	-0.41	-0.40	-0.40	0.65	0.63	0.92	-0.91	-0.93	-0.86	1.48	**1.90**	**2.01**
Test 3	-0.34	-0.34	-0.34	0.73	0.72	0.70	-0.56	-0.47	**-0.19**	1.16	**1.86**	**2.20**
Test 4	-0.35	-0.35	-0.36	0.71	0.78	1.03	-0.99	-0.99	-0.89	0.80	1.17	1.48
Test 5	-0.37	-0.37	-0.38	0.57	0.62	0.76	-0.88	-0.84	-0.81	0.73	1.03	1.45
Test 6	-0.41	-0.40	-0.39	1.01	1.06	1.15	-0.69	-0.60	**0.06**	1.06	**1.66**	**2.11**
Test 7	-0.39	-0.39	-0.36	0.72	0.83	0.68	-0.91	-0.94	-0.78	0.49	0.91	1.40
Test 8	-0.36	-0.36	-0.37	1.03	1.05	0.98	-0.92	-0.87	-0.70	0.93	**1.51**	**1.62**
Test 9	-0.37	-0.39	-0.40	0.92	0.76	0.60	-0.68	-0.63	-0.77	1.13	**1.74**	**1.87**
Test 10	-0.43	-0.44	-0.45	0.89	0.71	0.73	-0.93	-0.67	-0.48	1.40	**1.88**	**1.96**
Det Rate	0%	0%	0%	0%	0%	0%	0%	0%	20%	0%	60%	60%
	POINT C						POINT D					
	Static DSF			Data-Driven DSF			Static DSF			Data-Driven DSF		
Threshold	$DSF_{97.5\%}$ = (-0.16, 1.43)			$DSF_{97.5\%}$ =1.51			$DSF_{97.5\%}$ = (-1.73, 1.37)			$DSF_{97.5\%}$ =1.48		
Area Lost	0%	0.5%	1.5%	0%	0.5%	1.5%	0%	0.5%	1.5%	0%	0.5%	1.5%
Test 1	0.05	-0.08	**-0.31**	0.96	1.30	**1.83**	-0.98	-0.96	-0.91	0.92	1.15	1.38
Test 2	0.92	0.92	0.68	1.26	1.37	**2.24**	-0.98	0.63	-0.67	1.21	1.29	**2.12**
Test 3	0.91	0.91	0.72	1.10	1.19	**2.42**	0.05	0.15	-0.41	0.93	0.87	**1.61**
Test 4	0.79	0.84	0.94	0.58	0.97	**1.90**	-0.99	-0.98	0.98	0.72	1.06	1.26
Test 5	0.84	0.87	0.83	0.73	1.00	**1.74**	0.35	0.22	-0.50	0.73	1.05	**1.69**
Test 6	0.82	0.87	0.88	0.95	**1.79**	**2.44**	0.23	-0.01	-0.51	0.82	1.28	**1.92**
Test 7	0.85	0.60	-0.03	0.62	1.43	**2.27**	-0.95	-0.94	-0.90	0.92	1.17	**1.56**
Test 8	0.96	0.97	0.84	1.08	1.25	**1.98**	-0.96	-0.95	-0.87	0.67	0.80	1.33
Test 9	0.85	0.80	0.54	0.99	1.30	**1.66**	0.97	0.97	0.97	1.02	0.79	0.98
Test 10	0.31	0.13	**-0.27**	1.28	**1.87**	**3.00**	-0.98	-0.98	-0.90	1.23	1.27	1.47
Det Rate	0%	0%	20%	0%	20%	100%	0%	0%	0%	0%	0%	50%

4.2 DSFs for Heterogeneous Representations

Thus far, the utility of a data-driven DSF has been demonstrated for homogeneous representations (AR model of acceleration only). However, since it has been shown that the combination of surface strain and acceleration data through the bivariate autoregressive model not only provides a more accurate signal representation (see Fig. 2), but also enhances damage detection in comparison with the use of either strain or acceleration alone[1,2], the data-driven DSF in equation (5) is modified for a heterogeneous representation to better exploit the most sensitive bivariate AR coefficients:

$$DSF_k = \max\left[\left| \frac{\alpha_{ik} - \underset{ref}{avg}[\alpha_{ik}]}{\underset{ref}{std}[\alpha_{ik}]} \right|_{i=1:Na}, \left| \frac{\beta_{jk} - \underset{ref}{avg}[\beta_{jk}]}{\underset{ref}{std}[\beta_{jk}]} \right|_{j=0:Nb} \right] \quad (7)$$

To demonstrate the performance of the DSF in equation (7), damage detection results are compared between it and its homogeneous counterpart, equation (5), using the same demonstrative cases in Section 4.1. The damage detection results are shown in Table 2, where bold-faced values again indicate that damage is detected for $DSF_k > DSF_P$. Results are compared to the homogeneous data-driven DSF, as extracted from Table 1.

From Table 2, several important conclusions can be drawn about the heterogeneous formulation:

1. Incidence of false positives for the heterogeneous approach (Eq. 7) 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 (Eq. 7). The reason for the stark contrast in performance between the heterogeneous and homogeneous approaches can explained as follows: locations A and B, though being near the damage zone, are characterized by comparatively low acceleration responses; however, the surface strains at these points are comparatively higher than points C and D. Thus 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 that adapts to the response component most critical at that location.
3. Consistent with the homogeneous scheme, the heterogeneous DSF's (Eq. 7) detection rate falls off further from the damage location for the smaller of the two damage scenarios. Still its reliability is 100% for the smaller of the two damage cases at points A and B.
4. Like their homogeneous counterparts, the heterogeneous DSF (Eq. 7) values increase with the damage level and proximity to the damage location. As expected, the data-driven DSF (Eq. 7) takes on its largest values at points A and B, demonstrating its localization capability.

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. Thus, equation (7) is termed a *Bivariate Regressive Adaptive Index (BRAIN)* for damage detection within a decentralized, wireless sensor network. As discussed previously in Section 3.4, BRAIN is couched within a larger multi-scale wireless sensor network concept that employs a restricted network activation scheme (RINAS) to insure that more sophisticated two-stage models are not required to accommodate variability in operational and environmental states [2]. Under such conditions, BRAIN provides not only reliable detection, but significantly less computational effort and memory requirement due to the limited number of reference pool parameters stored locally.

5. CONCLUSIONS

A time domain, bivariate autoregressive damage detection method called BRAIN is presented. Its novel feature is a data-driven DSF operating on heterogeneous data pairs of strain and acceleration. This study demonstrated a number of important features of BRAIN in comparison with other homogeneous damage detection methods currently available using simulations of a randomly-excited, thin beam. These findings speak not only to the flexibility offered by a data-driven DSF but also the enhanced sensitivity to damage facilitated by a heterogeneous approach to detection. Some of the key features of BRAIN demonstrated in this study are:

1) The underlying BAR model offers a more accurate representation of the acquired acceleration signals.
2) Dramatic reduction in required on-board memory, but also any computation (and power drain) associated with the manipulation of a reference database since only a few key statistics of the reference pool's AR coefficients and a pre-defined statistically significant threshold are required for damage detection.
3) No enhanced susceptibility to false positives.

Table 2. Detection results of homogeneous and heterogeneous data-driven DSF

	POINT A						POINT B					
	Homogeneous			Heterogeneous			Homogeneous			Heterogeneous		
Threshold	$DSF_{97.5\%}$ =1.49			$DSF_{97.5\%}$ =1.49			$DSF_{97.5\%}$ =1.49			$DSF_{97.5\%}$ =1.53		
Area Lost	0%	0.5%	1.5%	0%	0.5%	1.5%	0%	0.5%	1.5%	0%	0.5%	1.5%
Test 1	1.01	1.04	1.06	**1.91**	**32.44**	**136.29**	0.99	1.04	1.38	1.27	**2.68**	**5.78**
Test 2	0.65	0.63	0.92	1.34	**31.76**	**137.10**	1.48	**1.90**	**2.01**	0.62	**3.52**	**4.88**
Test 3	0.73	0.72	0.70	1.22	**33.12**	**139.32**	1.16	**1.86**	**2.20**	1.14	**2.62**	**4.71**
Test 4	0.71	0.78	1.03	0.69	**32.47**	**136.04**	0.80	1.17	1.48	0.53	**3.54**	**4.93**
Test 5	0.57	0.62	0.76	0.41	**32.70**	**136.51**	0.73	1.03	1.45	0.31	**2.53**	**4.62**
Test 6	1.01	1.06	1.15	0.80	**33.66**	**139.28**	1.06	**1.66**	**2.11**	0.82	**2.52**	**4.93**
Test 7	0.72	0.83	0.68	0.68	**32.77**	**137.29**	0.49	0.91	1.40	0.97	**3.18**	**4.69**
Test 8	1.03	1.05	0.98	0.61	**32.22**	**136.28**	0.93	**1.51**	**1.62**	0.69	**3.55**	**5.04**
Test 9	0.92	0.76	0.60	1.15	**32.40**	**137.05**	1.13	**1.74**	**1.87**	1.02	**2.48**	**4.70**
Test 10	0.89	0.71	0.73	1.25	**31.63**	**134.34**	1.40	**1.88**	**1.96**	1.00	**3.01**	**4.70**
Det Rate	0%	0%	0%	10%	100%	100%	0%	60%	60%	0%	100%	100%
	POINT C						POINT D					
	Homogeneous			Heterogeneous			Homogeneous			Heterogeneous		
Threshold	$DSF_{97.5\%}$ =1.51			$DSF_{97.5\%}$ =1.47			$DSF_{97.5\%}$ =1.48			$DSF_{97.5\%}$ =1.53		
Area Lost	0%	0.5%	1.5%	0%	0.5%	1.5%	0%	0.5%	1.5%	0%	0.5%	1.5%
Test 1	0.96	1.30	**1.83**	1.27	1.39	**1.92**	0.92	1.15	1.38	1.27	**1.63**	**2.69**
Test 2	1.26	1.37	**2.24**	0.62	0.93	**1.69**	1.21	1.29	**2.12**	0.62	0.88	1.51
Test 3	1.10	1.19	**2.42**	1.14	1.16	**2.22**	0.93	0.87	**1.61**	1.14	1.17	**2.07**
Test 4	0.58	0.97	**1.90**	0.53	0.89	**1.78**	0.72	1.06	1.26	0.53	1.25	**2.03**
Test 5	0.73	1.00	**1.74**	0.31	0.59	**1.82**	0.73	1.05	**1.69**	0.31	1.33	**2.33**
Test 6	0.95	**1.79**	**2.44**	0.82	1.15	**1.89**	0.82	1.28	**1.92**	0.82	1.28	**2.72**
Test 7	0.62	1.43	**2.27**	0.97	1.30	**2.12**	0.92	1.17	**1.56**	0.97	0.55	**1.74**
Test 8	1.08	1.25	**1.98**	0.69	0.75	**1.68**	0.67	0.80	1.33	0.69	1.12	**2.04**
Test 9	0.99	1.30	**1.66**	1.02	1.00	**1.72**	1.02	0.79	0.98	1.02	1.31	**2.33**
Test 10	1.28	**1.87**	**3.00**	1.00	0.98	**1.84**	1.23	1.27	1.47	1.00	1.38	**1.92**
Det Rate	0%	20%	100%	0%	0%	100%	0%	0%	50%	0%	10%	90%

4) Marked improvement in detection rates due to the inclusion of strain and acceleration data.

5) Vast improvement in detection capability in the vicinity of damage, largely credited to the heterogeneous framework that recognizes the fact that structural response cannot be characterized by acceleration alone and a DSF that adapts to the response component most critical at that location.

6) Increasing DSF values with damage level and proximity to the damage location, demonstrating its localization and even extent-assessment capabilities.

Although further validation on more complex, experimental assemblies is required and is being conducted by the authors, these simulation studies indicate that the BRAIN concept offers a more reliable and robust means of damage detection whose computational demands are consistent with the limited resources available within wireless sensor networks.

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