VOL. 4, NO. 3, MAY 2009 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

VIBRATION-BASED STRUCTURAL HEALTH MONITORING TECHNIQUE USING STATISTICAL FEATURES FROM STRAIN MEASUREMENTS

A. P. Adewuyi and Z. S. Wu
Department of Urban and Civil Engineering, Ibaraki University, Hitachi, Japan
E-Mail: apadewuyi@yahoo.co.uk

ABSTRACT

A statistical vibration-based damage identification algorithm to assess the stability of the measurement data, detect and locate damage in civil structures, where variability in response and modal parameters due to measurement noise and environmental influence is often inevitable, is presented in this paper. The method exploits the regression analysis of peak values of the magnitudes of frequency response function (FRF) of target sensors relative to the reference wherein the statistical features are employed for data reliability assessment and damage localization. Through experimental investigation of a flexural structure using conventional strain gauges and long gauge fiber Bragg gratings (FBG) sensors, the importance of the technique for civil SHM is established and presented in an easy-to-interpret graphical format for effective implementation of results. The statistical approach is very effective for damage localization using strain data.

Keywords: damage identification, statistical features, measurement noise, dynamic strain, FBG sensors, structural health monitoring.

INTRODUCTION

Progressive deterioration of civil infrastructure begins once they are built and subjected to normal continuous and occasional excessive loading, and adverse environmental conditions. Because the intrinsic changes that adversely affect the immediate or future performance of a structural system are usually unknown *a priori*, prompt and intensive monitoring of structural systems is very important. The extension of vibration-based damage identification (VBDI) techniques to civil infrastructure is increasingly receiving attentions because of rise in social and economic demands for structural integrity and safety. During the past few decades, a significant amount of research has been conducted in the area of nondestructive damage detection via changes in modal responses of a structure. A number of model-free damage identification techniques have been developed and successfully investigated primarily because of they are computationally simple without any need for an updated numerical model. Most notable among these techniques are based on natural frequency, mode shape curvatures, modal flexibility and its derivatives, modal stiffness, modal strain energy, frequency response function and its curvature, and power spectral density (PSD). Physical quantities most relevant and sensitive to the structural properties of interest are selected for monitoring purposes. Extensive literature reviews and advances on VBDI have been reported by Doebling *et al*. (1996), Sohn *et al*. (2003) and Carden and Fanning (2004). Li and Wu (2008) and Wu and Li (2007) also develop modal macro-strain vector (MMSV) method of damage identification using the modal parameters extracted from dynamic macro-strain data recorded by arrays of long-gauge FBG sensors distributed throughout the full or some partial areas of the flexural structures.

Despite the numerous achievements made so far, the search for more reliable strategies for both damage localization and quantification in large-scale civil structures is still in progress due to inevitable variability in measurement data as a result of measurement error and environmental factors. So, the ability to correctly distinguish changes in the modal properties caused by damage from those arising from variations in the measurements induced by electrical noise and other environmental conditions is an essential issue requesting serious attention for successful civil SHM. Thus, the process of vibration-based SHM can be fundamentally considered as that of statistical pattern recognition. In quest for statistical damage identification algorithms that would take into consideration all the aforementioned factors, Pape (1993) proposes a technique to identify damaged parts using statistical methods and measured natural frequencies. Damages are detected by assessing resonant frequencies that fall outside the mean standard deviations. The shortcoming of the approach is its inability to detect smaller defects. Brincker *et al*. (1995) use a statistical analysis method independent of the knowledge of the input signal to detect damage in two concrete beams with different reinforcement ratios using changes in the measured vibration frequencies. The method is based on significance indicator for any modal frequency or damping ratio determined by scaling the observed changes by the estimated standard deviation of the parameters or a unified significance indicator expressed as the summation of frequency and damping significance indicators over several measured modes. It was noted that measured modal parameters with high confidence are weighted more heavily in the indicator function. Similar to other frequency-based damage identification methods, the significance indicator proved to be a sensitive structural damage indicator, but incapable to localize damage. Doebling and Farrar (1997) develop a statistical procedure that uses measured coherence functions to estimate the uncertainty bounds on the magnitude and phase of the frequency response functions (FRFs), and prorogate the uncertainty to modal parameters.

In this study, a statistical VBDI algorithm based on the regression analysis of peak values of the magnitudes of FRF of target sensors relative to the reference is presented for data reliability assessment and damage localization. The proposed method is suitable for civil SHM, where variability in response and modal parameters due to measurement noise and environmental influence is often inevitable, to assess data quality prior to damage identification. Also, the ability to effectively manage and make sense of enormous amounts of data collected under continuous monitoring process for an effective diagnostic and/or prognostic system is an added advantage. The effectiveness of the method is established though experimental investigations on a flexural structure by using strain gauges and long-gauge fiber Bragg grating (FBG) strain sensors.

VIBRATION-BASED STRUTURAL HEALTH MONITORING USING STATISTICAL FEATURES

Farrar *et al*. (1999) describe the process of SHM as fundamentally one of statistical pattern recognition. A successful civil SHM program involves selection and placement of sensors suitable for measurement of key parameters that influence the performance and health of the structural system. This section presents a vibration-based damage identification algorithm using statistical features extracted from continuous monitoring of dynamic measurement data for a reliable practical application to civil infrastructure.

Theoretical background

From experimental modal analysis (EMA), the strain frequency response functions (FRFs), $H^{d}_{jk}(\omega)$ between the applied force and measured strain responses can be expressed as

$$H^{\varepsilon}_{jk}(\omega) = \sum_{r} \frac{{}_r\psi_j \cdot {}_r\phi_k}{M_r(\omega_r^2 - \omega^2 + i2\xi_r\omega_r\omega)} \tag{1}$$

where ${}_r\psi_j$ represents the r^{th} strain mode shape respectively at response measurement point j; and ${}_r\phi_k$ is the mode shape component of displacement mode r at excitation point at k^{th} DOF. M_r is the modal mass and ξ_r is the modal damping ratio.

Additionally, the magnitude of strain FRF at resonance for any mode is given by

$$\left|H^{d}_{jk}(\omega = \omega_r)\right| = \left(\frac{{}_r\phi_k}{2M_r\xi_r\omega_r^2}\right){}_r\phi_j \tag{2}$$

It is obvious from equation (2) that for a given mode, the quantity $\frac{{}_r\phi_k}{2M_r\xi_r\omega_r^2}$ is a constant for all response measurements at different locations on the structure due to the same applied excitation at k^{th} DOF.

Most damage identification techniques are developed on the assumption of linear structural behavior in the pre- and post-damage states. Therefore, dynamic responses are very suitable for modal parameter superposition applications. The frequency response functions can be obtained through fast Fourier transforms (FFT). By considering m measurement points for the displacement transducers and strain sensors at any given mode, the peak values of FRF magnitude of the displacement response data referred to as modal strain vector (MSV) extracted from the peak values of FRF magnitude of the strain response data is given by

$$\mathrm{MSV} = \left\{ {}_r\psi_1 \quad {}_r\psi_2 \quad \ldots \quad {}_r\psi_j \quad \ldots \quad {}_r\psi_m \right\}^T \tag{3}$$

The strain mode shape at a particular measurement point relative to a reference sensor of same type mounted at an undamaged location is linear and of constant slope. Any deviation in this feature is an indication of changes in the dynamic properties of the structure due to damage. The reference strain sensors denoted by ${}_r\psi_{ref}$ should be carefully selected from any of the m sensors located at points with the least possibility of damage. In flexural structures, for example, the reference sensor could be placed at regions of low bending moment.

Because measurement data can be measured under different conditions, the ability to normalize the data becomes very central to the damage detection process. In this case, the MSV is normalized by the modal response of the reference sensor. This approach is meant to minimize to the extent possible the variability in the data acquisition process. Thus, the normalized MSV with respect to the reference sensors is given by:

$$\left\{\lambda_{1r} \quad \lambda_{2r} \quad \ldots \quad \lambda_{(m-1)r} \quad \lambda_{mr}\right\} = \left\{ \frac{{}_r\psi_1}{{}_r\psi_{ref}} \quad \frac{{}_r\psi_2}{{}_r\psi_{ref}} \quad \ldots \quad \frac{{}_r\psi_{(m-1)}}{{}_r\psi_{ref}} \quad \frac{{}_r\psi_m}{{}_r\psi_{ref}} \right\} \tag{4}$$

For long-gauge FBG sensors, the mathematical expressions for conventional strain measurement are still very applicable except that the modal strain now becomes modal macro-strain (MMS). Further information on packaging and performance of long-gauge FBG sensor can be obtained from Li and Wu (2007). The developed sensors are characterized by the capability of obtaining the measurements by integrating both local and global information due to the fact that strain is a typical local response and distributed sensor placement helps to record the data covering the large region of a structure. Moreover, distributed strain sensing technique also reduces the number of unknown parameters for effective analysis of measured data.

Data interpretation and features extraction

The study of data features required to distinguish the damaged structures from undamaged ones has received considerable attention in the technical literature. Any SHM monitoring system will produce an enormous amount of data from which it will be necessary to select the appropriate information. An innovative analysis of measured data and accurate interpretation of extracted features possess essential ability that makes sense of the enormous amounts of data collected during monitoring exercise for an effective diagnostic and/or prognostic system. This supplies useful information that is meaningful to bridge owners, inspectors and engineers for practical implementation and effective management of civil infrastructure. A 3-step damage identification algorithm that evaluates the stability of measurement data and localizes damage in flexural structures using statistical features is summarized in Figure-1. Inherent in the feature selection process are the ability to identify the performance of sensors and effectively condense data. In addition, provisions are made for automatic updating of previous data if the features remain unchanged, while damages are localized at the sensor locations characterized by feature changes.

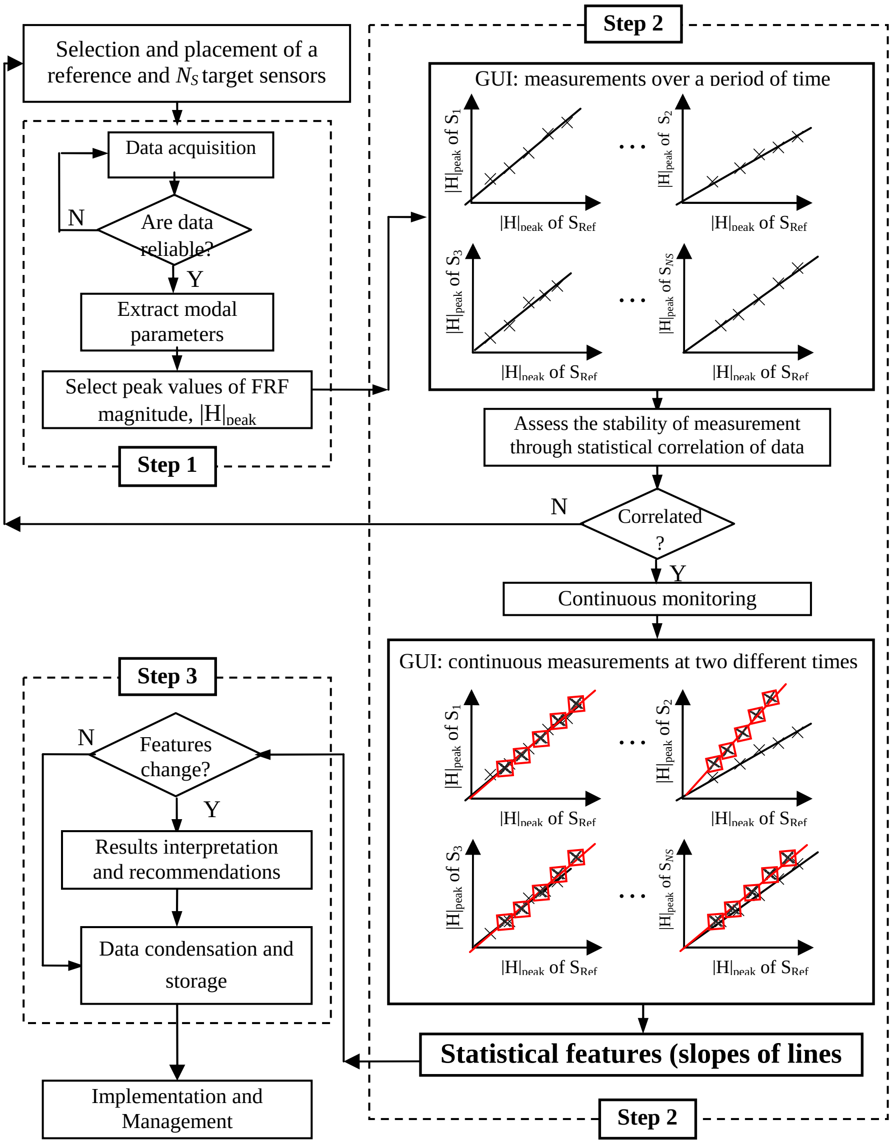

Figure-1. Flowchart for structural health monitoring program using statistical features.

The 3-step algorithm for data interpretation and feature extraction based on dynamic measurement data from different types of sensing techniques as presented in Figure-1 is described as follows:

VOL. 4, NO. 3, MAY 2009 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

(1) Selection and placement of adequate reference sensor S_{Ref} and target sensors S_{Ns} (Ns = 1, 2 … m) suitable for measuring key parameters that influence the performance and health of the structural system are made. Modal parameters are extracted for each measurement after satisfactory preliminary assessment of the reliability of the data acquisition systems. The peak values of the magnitude of the FRF for each measurement data are obtained in a way similar to the construction of eigenvector in modal analysis.

(2) From the records of several measurement data at a particular state of the structure, a graphical user interface is created, which consists of m charts corresponding to the plots of peak values of the magnitude of the FRF of target sensors at *y* axis against that of the reference sensor at *x* axis. The consistency of the measurement data obtained from different sensing techniques can be assessed through the statistical correlations for each structural condition. For continuous measurements at any two different times, comparative plots of peak values of FRF magnitudes are made to assess the variations in the slopes of lines of fit. Strain as a very sensitive local response can correctly localize damages at sensor points by comparing two consecutive slopes of lines of fit.

(3) If the slope increases, damage is localized at the region of the sensor. No change in structural condition is indicated by constant slope, while slope reduction is an implication of damage at the location of the reference sensor. The deviation of slope of the fit lines from the initial value is clearly a statistical feature for damage identification. Condensation of huge data is guaranteed by the technique and the data storage devices are more easily and effectively managed. Subsequent data collected from undamaged regions conveniently replace the previous, and the time-history data and important features immediately before and after damage are also saved. The results are easy to interpret and appropriate recommendations can be made for effective management and implementation.

EXPERIMENTAL INVESTIGATION

Experimental set-up and data collection

To demonstrate the proposed technique experimentally, three $50\times3\times960$ mm^3 simply supported steel beam specimens shown in Figure-2 were used. To contrast FE model, the beam was modeled by 16 elements, 17 nodes and 32 degrees of freedom. The Young's modulus and the density of the specimens are 2.10×10^{11} N/m^2 and 7862 kg/m^3 respectively. Damage was simulated by introducing width reductions from 50mm to 24mm for single damage at element 6 and double damages at elements 6 and 10. The intact, single and double damage cases are respectively denoted as C1, C2 and C3.

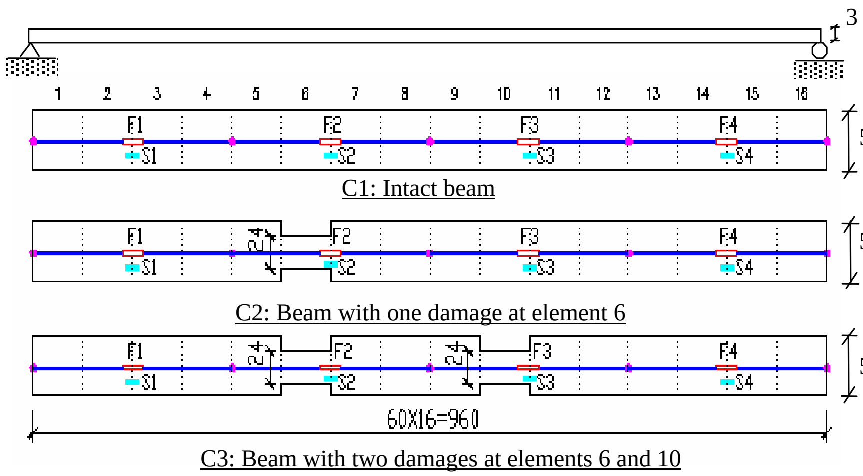

Figure-2. Experimental specimens and sensor placement.

A succession of single-point impact loads was applied at arbitrary locations on the beams to simulate loading with a high bandwidth. Such tests were performed 15 times and the measured data were used for modal identification. The dynamic responses were collected using four long-gage FBG sensors (F1~F4) of 240mm gauge length attached to the bottom surface of the specimens and four conventional strain gauges (S1~S4) of 5mm gauge length for comparison. In order to compare strain measurements between conventional strain gauges and the long-gauge FBG sensors, the two types of instruments were systematically installed such that their centers coincide.

The dynamic responses from FBG sensors and strain gauges were recorded at a sampling rate of 250Hz and 500Hz, respectively; and impulsive excitations by impact hammer recorded at 500Hz. The FRF was obtained from the spectral densities of the force input and response outputs at each measurement point. The FRF can be calculated via the classical fast Fourier transforms (FFT) algorithms expressed as

$$H(\omega) = \frac{Z(\omega)F^*(\omega)}{F(\omega)F^*(\omega)} = \frac{S_{zf}(\omega)}{S_{ff}(\omega)} \tag{5}$$

Where $Z(\omega)$ and $F(\omega)$ are the FFTs of the response and force time domain signals, $z(t)$ and $f(t)$, and the asterisk denotes the complex conjugate. $S_{zf}(\omega)$ is the cross spectrum between the output and input signals; and $S_{ff}(\omega)$ is the auto-spectrum of the input signals. The symbols z and f denote the response signals and excitation signals, respectively. The approach was employed to reduce the effect of noise due to uncorrelated excitation.

Mode shapes were extracted using global curve-fitting techniques. Figure-3 shows that the mode shapes computed using ANSYS program and measured using FBG sensors have good agreements.

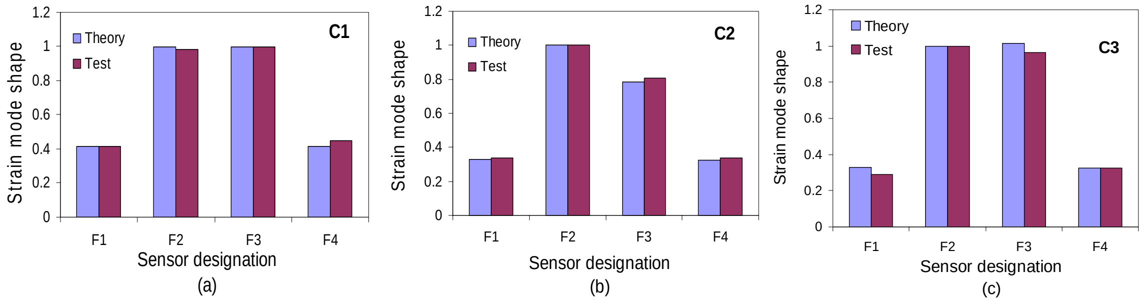

Figure-3. Theoretical versus experimental distributed strain mode shape for first mode.

DISCUSSION OF EXPERIMENTAL RESULTS

Table-1 gives the first modal frequency extracted from the response data of the three sensors for the different structural states. All the data perfectly agree with high precision.

Table-1. Identified resonant frequencies using different sensors.

Scenarios	**Resonant frequencies** (Hz)	
	FBG sensors	**Strain gauges**
C1	6.021	6.021
C2	5.822	5.825
C3	5.638	5.637

The frequency spectra for the different measurement data under a typical excitation for the three structural cases C1, C2 and C3 measurement data are shown in Figures 4 and 5.

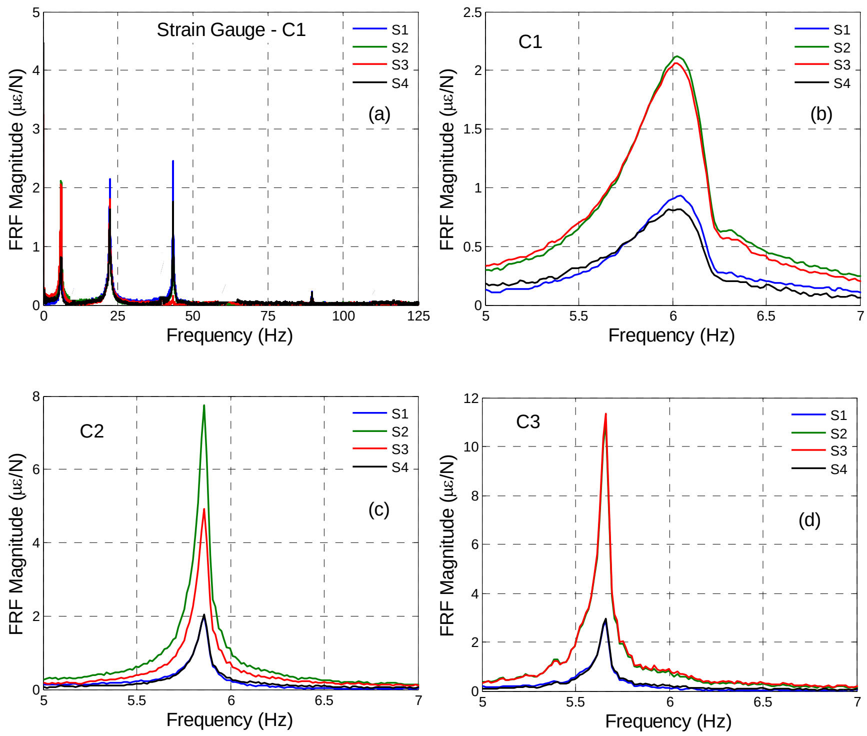

Figure-4. Typical frequency response spectra from strain gauges.

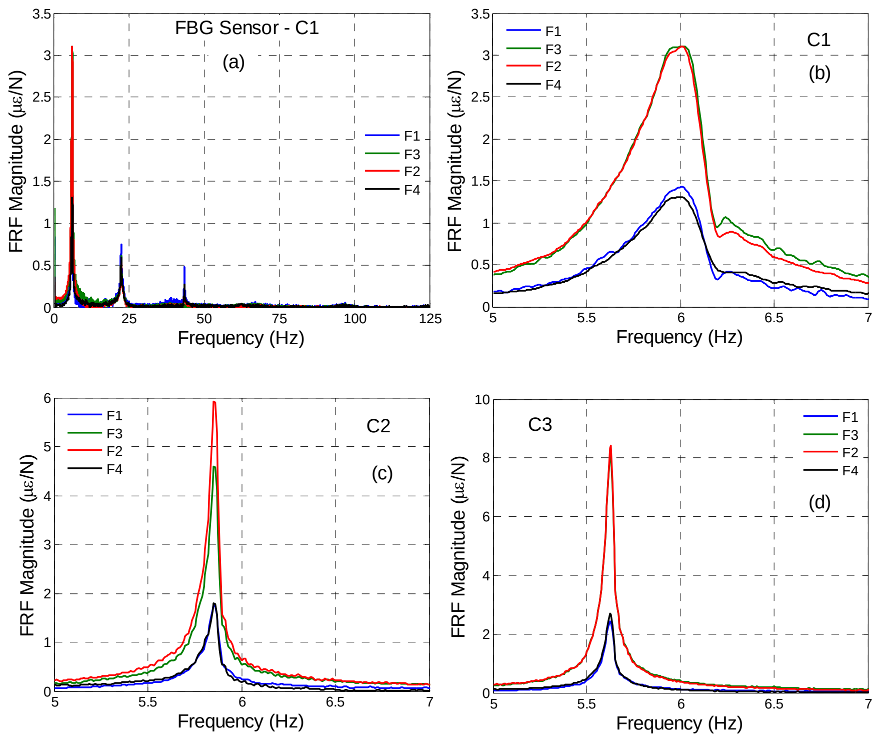

Figure-5. Typical frequency response spectra measured with long-gage FBG sensors.

By taking the first modal parameters into consideration, it is evident from the figures that the natural frequencies and the damping ratios reduce with increase in the damage extent. The stability of the measurements can be evaluated through the statistical correlation of the peak values of FRF magnitudes of the target sensors relative to that of the reference sensor. The reference sensors for this investigation are strain gauge S4 and FBG sensor F4.

VOL. 4, NO. 3, MAY 2009 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

Figures 6 and 7 show the behavior of the modal parameters extracted from measurement data collected from the two sensor types under the random excitations of different magnitudes for the three structural conditions of the beam specimens. From the plots of the modal parameters of each sensor against the reference sensor, the linearity of the relationships for all excitation cases with single point impulsive load arbitrarily applied on the beams can be established for all the sensing techniques. By fitting the discrete points, good lines of fit implying stability of the measurements can be obtained.

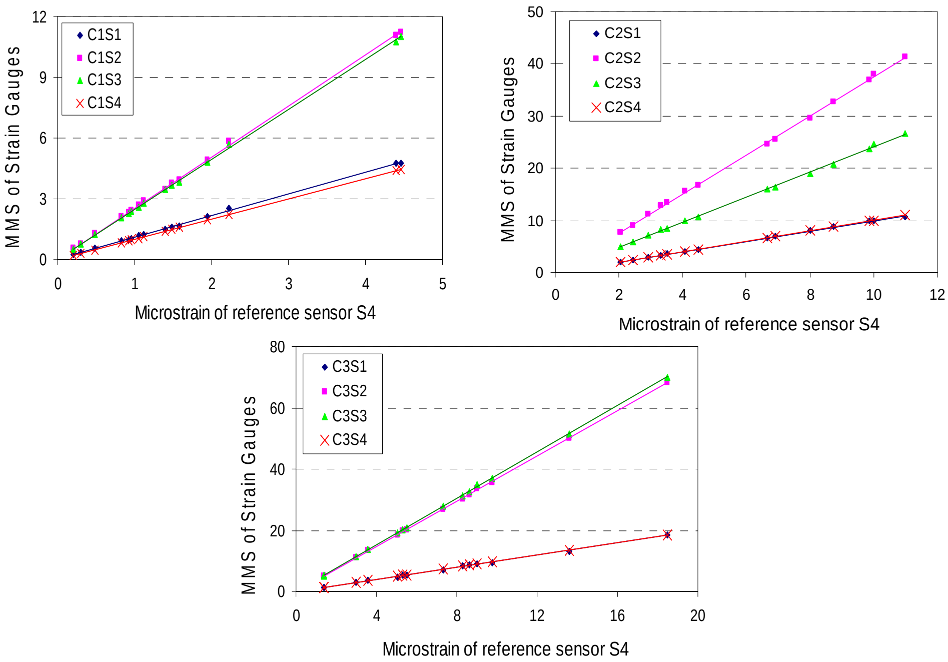

Figure-6. Modal strain parameter extracted from strain gauges.

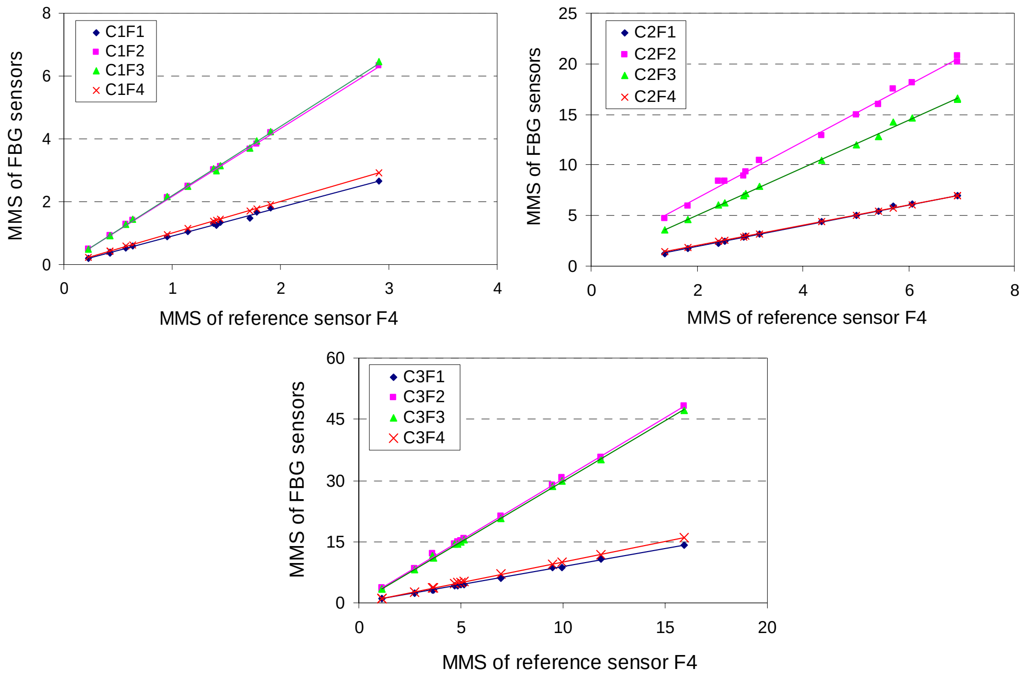

Figure-7. Modal macro-strain measurements from FBG sensors.

The stability of the measurement data is evaluated via the correlation of the modal data of each sensor type relative to its reference as shown in Table-2.

Table-2. Statistical correlation of modal parameters using different sensors.

Cases	**Correlation coefficients**					
	Strain gauges			**FBG sensors**		
	S1	S2	S3	F1	F2	F3
C1	0.9992	0.9996	0.9996	0.9964	0.9996	0.999
C2	0.9993	0.9993	0.999	0.9987	0.9964	0.9979
C3	0.9994	0.9998	0.9998	0.9997	0.9995	0.9995

It is clear that the measurement data from all the sensors have perfect statistical correlations with respect to the reference. These excellent correlation coefficients signify the stability and reliability of the response data measured by all the three sensors. It can be inferred that the effects of noise on the measurements is minimal.

Statistical feature for damage localization

The lines of fit have dual features: the correlation coefficient and the slope or equation of fit line. While the former assesses the consistency or stability of the data, the slope is employed to localize damage. A close monitoring of the variation of slopes of fit lines for each sensor corresponding to the structural scenarios under different excitations at any different times gives clear indication of location of damage. The plots of variation of slopes of fit lines for the two sensor types are shown in Figures 8 and 9. Table-3 gives the variation of slopes of lines of fit for strain gauges and FBG sensors in which the underlined figures in bold indicate the significant change indicating damages.

Table-3. Statistical features indicated by variation of slopes of fit lines.

Cases	**Slope of fit lines**					
	Strain gauges			**FBG sensors**		
	S1	S2	S3	F1	F2	F3
C1	1.145	6.3502	6.0371	0.916	4.738	4.911
C2	0.9781	14.178	5.8734	1.0209	8.827	5.1164
C3	0.9917	13.613	14.31	0.8934	9.099	8.781

The variation of slope of fit lines corresponding to the strain gauges S2 and S3 clearly localized the damage as shown in Figure-8. The plots are made on similar scale for easy comparison of the structural condition at the location of sensors. It is evident from Figure 8a that there is no significant change in the slope of strain gauge S1, which implies that no damage has taken place within the coverage of the sensor. However, damages are clearly localized at the locations sensors S2 and S3 as indicated by increase in slopes of fit lines in Figures 8b and 8c. Damages for scenario C2 is located close to sensor S2, while damage scenario C3 is located in the region of sensor S2 and S3. The statistical damage identification method has reaffirmed that strain is very sensitive response to local damage. However, strain gauges cannot reflect influence of damage effectively unless they are located at the damaged region. Moreover, the challenges of huge data acquisition and processing costs, durability and long-term reliability render strain gauges unfit for large-scale civil SHM.

VOL. 4, NO. 3, MAY 2009 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

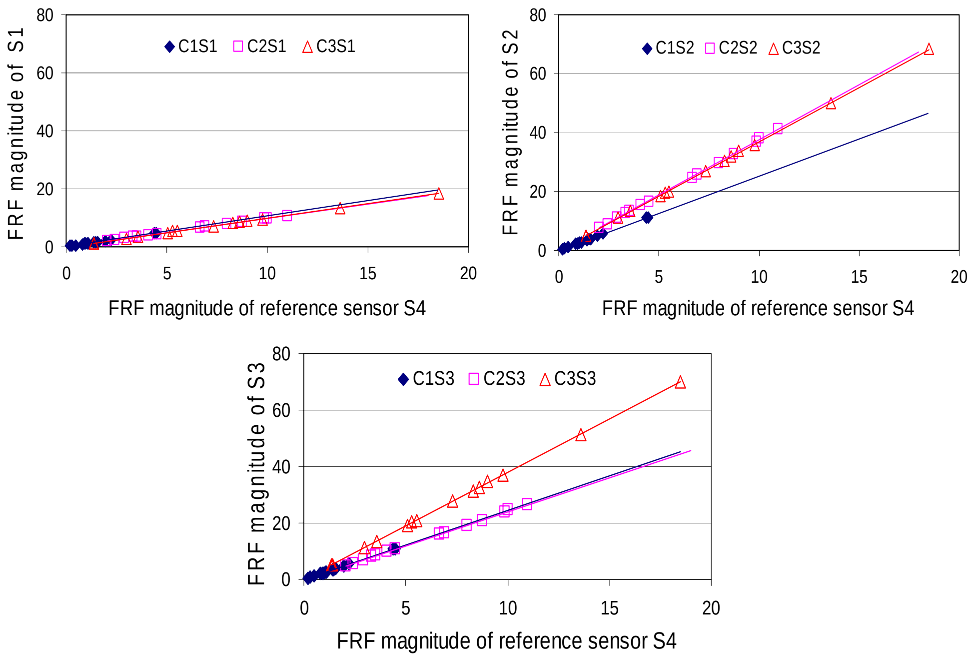

Figure-8. Variation of slopes of fit lines for strain gauges.

Similar to strain gauge measurements, damages are evidently localized by FBG sensors F1 and F3 as shown in Figure-9.

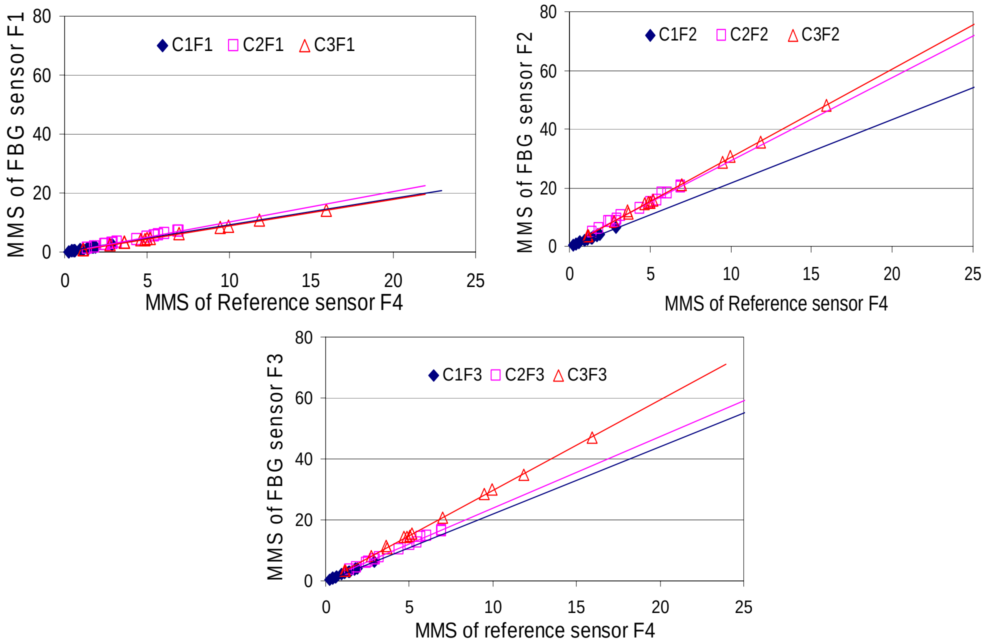

Figure-9. Variation of slopes of fit lines for FBG sensors.

There is no appreciable change in slope of sensor F1 in Figure-9a while Figures 9b and 9c show indications of damage in the regions covered by sensors F2 and F3. Damages for scenarios C2 and C3 are located within the gauge length of sensor F2 and damage scenario C3 is located within sensor F3. One of the benefits of distributed strain sensing technique over the conventional strain gauge is that every critical section of the structure is covered without any loss of vital information for damage identification.

CONCLUSIONS

A damage identification strategy adaptable to civil structures using statistical features of dynamic strain measurements has been presented and verified through experimental study. The method has the capability to reliably assess the consistency of the measurement data, promptly identify faulty sensors and accurately locate damages in structure by using statistical features. The importance of the technique for civil SHM was established by using both point and distributed strain data and presented in an easy-to-interpret graphical format for effective implementation. The stability of all measurement data was perfectly determined via the correlation of modal parameters of target sensor with the reference. The ability of strain gauges to correctly locate damage is limited to its short gage length, while the long-gage FBG sensors are more efficient choice for effective identification and localization of damage.

REFERENCES

Brincker R., P. Anderson, P.H. Kirkegaard and J.P. Ulfkjaer. 1995. Damage Detection in Laboratory Concrete Beams. Proceedings of the 13th International Modal Analysis Conference. pp. 668-674.

Carden P.E. and P. Fanning. 2004. Vibration Based Condition Monitoring: A Review. Structural Health Monitoring. 3(4): 355-377.

Doebling S.W. and C.R. Farrar. 1997. Using Statistical Analysis to Enhance Modal-Based Damage Identification. Structural Damage Assessment Using Advanced Signal Processing Procedures. Proceedings of DAMAS 97 University of Sheffield, UK. pp. 199-210.

Doebling S.W., C.R. Farrar, M. B. Prime and D. W. Shevita. 1996. Damage identification and health monitoring of structural and mechanical systems from changes in their vibration characteristics: A literature review. Los Alamos National Laboratory Report.

Farrar C.R., T.A. Duffey, S.W. Doebling and D.A. Nix. 1999. A Statistical Pattern Recognition Paradigm for Vibration-Based Structural Health Monitoring. Proceedings of the 2nd International Workshop on Structural Health Monitoring, Stanford, CA. Sept 8-10.

Li S.Z. and Z.S. Wu. 2007. Development of Distributed Long-gage Fiber Optic Sensing System for Structural Health Monitoring. Structural Health Monitoring. 6(6): 133-143.

Li S.Z. and Z.S. Wu. 2008. Modal Analysis on Macro-strain Measurements from Distributed Long-gage Fiber Optic Sensors. Journal of Intelligent Material Systems and Structures. 19(8): 937-946.

Pape D.A. 1993. A Modal Analysis Approach to Flaw Detection in Ceramic Insulators. Proceedings of the 11th International Modal Analysis Conference. pp. 35-40.

Sohn H., C.R. Farrar, F.M. Hemez, D.D. Shunk, D.W. Stinemates and B. R. Nadler. 2003. A Review of Structural Health Monitoring Literature: 1996-2001. Los Alamos National Laboratory Report. LA-13976-MS.

Wu Z. S. and S. Li. 2007. Two-level Damage Detection Strategy Based on Modal Parameters from Distributed Dynamic Macro-strain Measurements. Journal of Intelligent Material Systems and Structures. 18(7): 667-676.