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Research Paper

STRUCTURAL HEALTH MONITORING USING TIME SERIES METHOD COMBINING MODAL EXTRACTION TECHNIQUE

Gayathri V G[1], B Lakshmi K[2], Rama Mohan Rao[2], P Eapen Sakaria[1], and Nagesh R Iyer[2]

Corresponding author:* ***Gayathri V G* ✉ *gayathrivg1990@gmail.com*

Structural Health Monitoring (SHM) is a process of continuous evaluation of a civil infrastructure by collecting information from a sensor network installed in the structure. It involves the process of observation of the system using the responses from a set of sensors, the extraction of damage sensitive features and the analysis of these features to determine the current health of the structure. Blind Source Separation (BSS) is a powerful signal processing tool that is used to identify the modal responses and mode shapes of a structure using the knowledge of responses. Time series method is used to know about the modal responses using time series modals the prediction can be done. An error index is used to identify the damage instant. Once the damage instant is identified the undamaged and damaged parameters of the system can be identified. The identification of the damage instant and the location can be done in this proposed method.

Keywords: Structural Health Monitoring, Blind Source Separation, Sensors, Damage instant, Time Series Method

INTRODUCTION

Structural health monitoring problem is posed in a statistical pattern recognition framework which consists of four-parts: (i) the evaluation of a structure's operational environment; (ii) the acquisition of structural response measurements; (iii) the extraction of features that are sensitive to damage; and (iv) the development of statistical models for feature discrimination. This damage detection approach has shown great promise in the identification of damage.

The various levels in the SHM process are as mentioned below.

Level 1: Damage detection - Determination of the damage present in the structure.

Level 2: Damage localization - Determination of the geometric location of the damage.

Level 3: Damage quantification - Quantification of the severity of the damage.

Level 4: Remaining life estimation - Prediction of the remaining service life of the structure.

[1] Department of Civil Engineering, Saintgits College of Engineering, Kottayam, Kerala, India.

[2] CSIR – Structural Engineering Research Centre, Chennai, Tamil Nadu, India.

Figure 1: Structural Health Monitoring – Overview

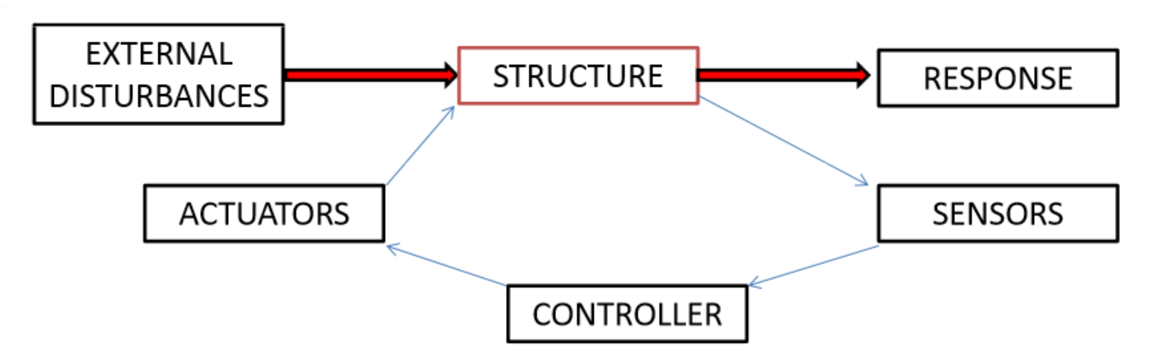
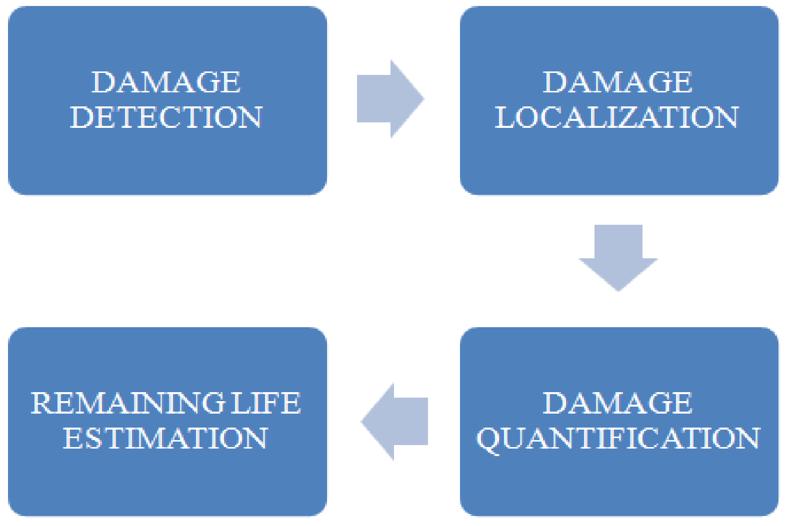


Figure 2: Levels of Structural Health Monitoring



LITERATURE REVIEW

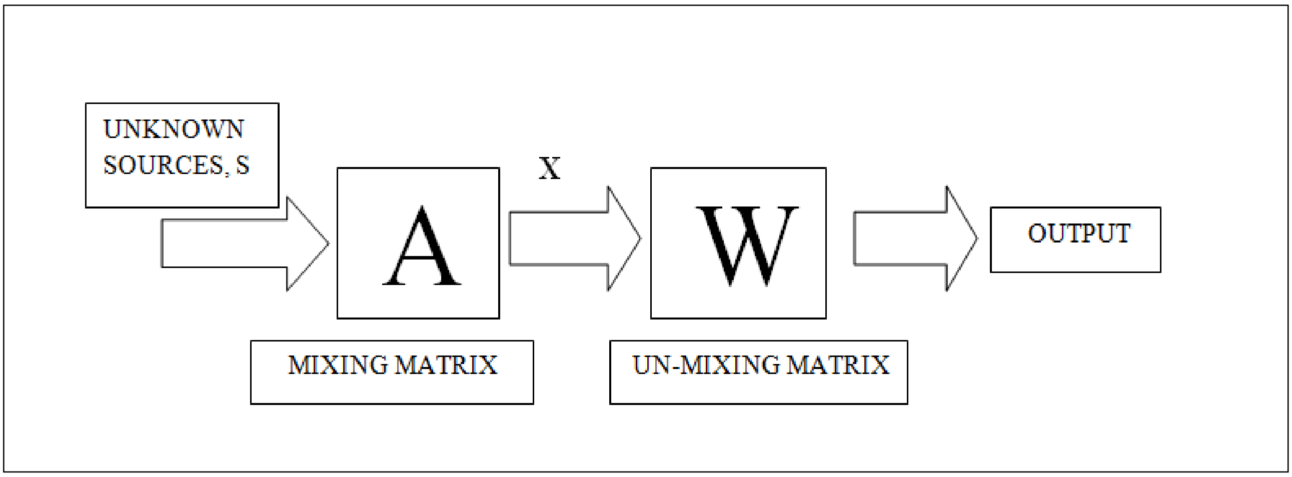
Sadhu and Hazra (2012) presented a novel damage detection algorithm is developed based on blind source separation in conjunction with time-series analysis. Blind Source Separation (BSS), is a powerful signal processing tool that is used to identify the modal responses and mode shapes of a vibrating structure using only the knowledge of responses. In the proposed method, BSS is first employed to estimate the modal response using the vibration measurements. Time-series analysis is then performed to characterize the mono-component modal responses and successively the resulting time-series models are utilized for one-step ahead prediction of the modal response. With the occurrence of newer measurements containing the signature of damaged system, a variance-based damage index is used to identify the damage instant. Once the damage instant is identified, the damaged and undamaged modal parameters of the system are estimated in an adaptive fashion. The proposed method solves classical damage detection issues including the identification of damage instant, location as well as the severity of damage. The proposed damage detection algorithm is verified using extensive numerical simulations followed by the full scale study of UCLA Factor building using the measured responses under Parkfield earthquake.

Ruigen Yao and Shamim N Pakzad (2012) presented a data-driven structural health monitoring based on sensor measurements. Modal parameters from system identification are the most widely studied structural state indicators adopted for this purpose; however, recent research has showed that they are not sensitive enough to local damage. In an effort to seek more effective alternatives, univariate autoregressive (AR) modeling on structural response has been investigated in several publications, where model characteristics are used as damage indices. Although these methods are generally successful, they tend to generate false alarms when the environmental conditions are varying because responses from only one location/sensor are considered. To strike a balance between sensitivity and stability, in this paper autoregressive with exogenous input modelling on measurements from several adjacent sensing channels is presented and applied to detect damage in a space truss structure. The damage feature is extracted from the residuals obtained via fitting the baseline model to data from the current structure. Also, damage localization is attempted by examining the estimated mutual information statistic between data from adjacent sensing channels.

Wenjia Liu *et al.* (2013**)** investigated the time series representation methods and similarity measures for sensor data feature extraction and structural damage pattern recognition. Both model-based time series representation and dimensionality reduction methods are studied to compare the effectiveness of feature extraction for damage pattern recognition. The evaluation of feature extraction methods is performed by examining the separation of feature vectors among different damage patterns and the pattern recognition success rate. In addition, the impact of similarity measures on the pattern recognition success rate and the metrics for damage localization are also investigated. The test data used in this study are from the System Identification to Monitor Civil Engineering Structures (SIMCES) Z24 Bridge damage detection tests, a rigorous instrumentation campaign that recorded the dynamic performance of a concrete box-girder bridge under progressively increasing damage scenarios. A number of progressive damage test case datasets and damage test data with different damage modalities are used. The simulation results show that both time series representation methods and similarity measures have significant impact on the pattern recognition success rate.

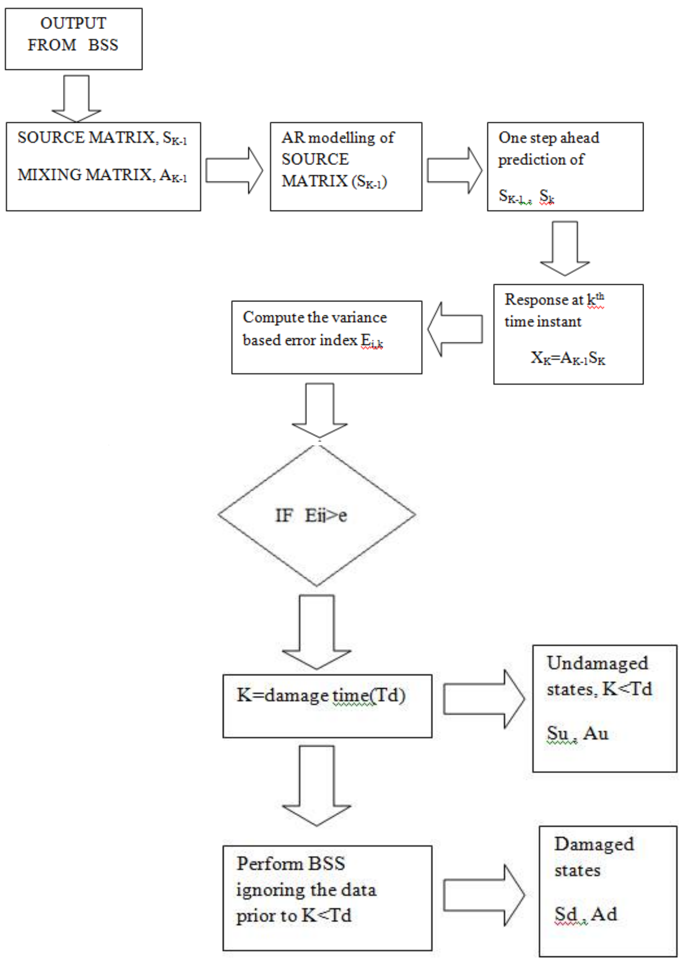
METHODOLOGY

The basic problem statement of BSS is given by BSS method along with the time-series analysis is proposed to detect the damage in the structural system. Time series models are used to characterize the sources that are obtained from the past observations and the future sources are predicted. An error is



evaluated between the true and predicted measurements and subsequently the damage is identified. With the arrival of newer measurements containing the signature of

Flowchart of the Proposed Method



structural damage, significant difference is observed between the predicted and true measurement, which is used as a damage indicator. Once the damage is detected, the measurements prior to the damage are discarded and the modal parameters of the damaged state are estimated based on the current measurements. The damage and undamaged modal parameters are estimated.

The method involves the following steps mainly

1. Estimation of the mixing matrix
2. Estimation of the source matrix
3. Time series modeling and one step ahead prediction of the sources
4. Identification of the damage location

FLOWCHART OF THE PROPOSED METHOD

Once the sources are extracted using the BSS method with the measurement up to (k – 1) th time instant, the sources can be predicted for k th time instant using their time-series models.

Where ϕ are the AR parameters

$$S_k = x\square_1 S_{k-1} + x\square_2 S_{k-2} + x\square_3 S_{k-3} + a_t$$

Once the sources are predicted, one-step ahead response can be estimated using:

$$x_{k1} = A_{k-1} S_k$$

where A_{k-1} is the mixing matrix based on the measurements up to $(k-1)$ th time instant. With the occurrence of new measurement at k th time instant, i.e, x_k the error between the predicted (i.e., x_{k1}) and true measurement (x_k) can be estimated. Therefore, by utilizing a suitable error index, damage can be estimated using the true and predicted measurement. The variance-based error index can be defined as:

$$Ei,k = \frac{R(0,k)-R1(0,k)}{R(0,k)}$$

$$R(0,k) = \sum_{n=0}^{k} x(n)/k,$$

$R(0,k) = \sum_{n=0}^{k} x1(n)/k$ are the variances of the true and the predicted measurement of i th floor location at k th time instant.

When the error index $E_{i,k}$ attains a value more than a specified tolerance e then it signifies that the modelling of s based on the measurements up to (k–1)th time instant is inappropriate. This particular scenario happens when there are significant changes in the system and leads to a situation when the damage occurs. Under such situation, the measurements up to (k–1)th time instant represents the system response of undamaged state. On the other hand, the current measurements hereby represent the response of damaged state. Therefore the measurements up to (k–1)th time instant (i.e., damage instant td) is separated out and the BSS method is employed separately to undamaged and damaged data sets to estimate the modal parameters of undamaged (Su, Au) and damaged system (Sd, Ad) respectively. In this way, time series analysis-based error index is implemented in the framework of BSS to characterize the successive damage and undamaged states.

Identification of Damage Location

Once the mode shapes of the damaged (Ad) and the undamaged (Au) systems are estimated, the damage location can be subsequently identified considering the difference between the modal co-ordinates of the mode shapes under undamaged and damaged condition. The following equations are used to find out the location damage:

Damaged states:

$$Z_d = \frac{\left(z_{d1} - 2z_{d2} + z_{d3}\right)}{S^2}$$

where z_{d1}, z_{d2}, z_{d3} are the modal coordinates for the successive time instants corresponding to the damaged mode shape matrix and S being the distance between the adjacent sensors in the structure.

Undamaged states:

$$Z_u = \frac{\left(z_{u1} - 2z_{u2} + z_{u3}\right)}{S^2}$$

where z_{u1}, z_{u2}, z_{u3} are the modal coordinates for the successive time instants corresponding to the undamaged mode shape matrix and S being the distance between the adjacent sensors in the structure.

RESULTS AND DISCUSSION

Case Study 1: Response of a 20-Storey Shear Building

The modal response of a 20-storey shear building was studied using the method of BSS. Sensors were placed in each storey. The acceleration data was generated choosing a particular storey to be damaged one. AR time series model was employed. The damage instant was detected and the modal curvatures for the damaged and undamaged responses were identified. The building response was studied under different signal noise levels and at different temperature conditions. Plots were made for the modal responses depicting the damage locations. The damage elements chosen include both single and multiple storeys. Both single and multiple damage locations were separately studied and plots depicting the damage locations were obtained

A typical storey damage matrix is shown below:

The damage storey was the tenth storey:

Damage Matrix

Sensor no	Mode (1)	Mode(2)	Mode (3)	Mode(4)	Mode(5)
1	0	0	0	0	0
2	7.54E-07	1.87E-06	0.000101	5.54E-05	0.000322
3	1.05E-06	8.77E-07	0.000122	7.83E-05	0.000134
4	1.34E-06	3.02E-06	0.000125	6.50E-05	0.00016
5	1.62E-06	5.07E-06	0.000104	3.40E-05	0.00043
6	1.89E-06	6.97E-06	6.29E-05	4.09E-06	0.000515
7	2.14E-06	8.66E-06	7.57E-06	3.83E-05	0.000334
8	2.37E-06	1.01E-05	5.33E-05	5.88E-05	6.50E-05
9	0.000358	0.000691	0.002117	0.000423	0.004237
10	0.000358	0.000706	0.002162	0.000459	0.004701
11	1.05E-06	2.05E-05	4.40E-05	2.50E-05	4.57E-05
12	1.23E-06	1.61E-05	2.25E-05	2.65E-05	0.000468
13	1.39E-06	1.15E-05	7.05E-05	1.14E-06	0.000672
14	1.55E-06	6.50E-06	9.88E-05	3.46E-05	0.00057
15	1.69E-06	2.87E-05	8.47E-05	5.55E-05	0.000484
16	2.45E-06	8.18E-06	0.000119	9.01E-05	0.000302
17	2.62E-06	1.70E-05	6.96E-05	6.44E-05	0.000604
18	2.74E-06	2.42E-05	9.86E-06	9.81E-06	0.000439
19	2.83E-06	2.93E-05	4.17E-05	5.33E-05	1.47E-05
20	0	0	0	0	0

Figure 3: Mode(1)

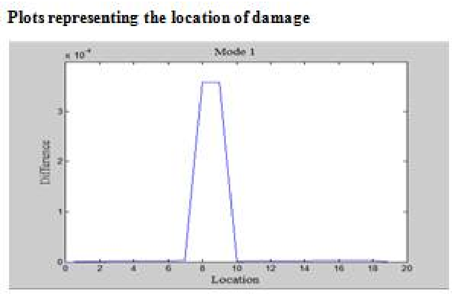


Figure 4: Mode(2)

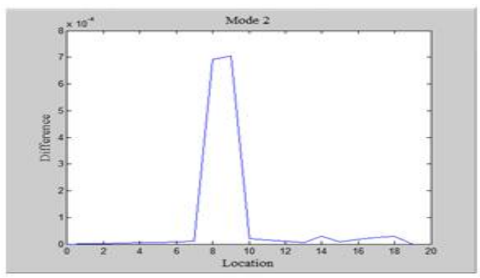


Figure 5: Mode(3)

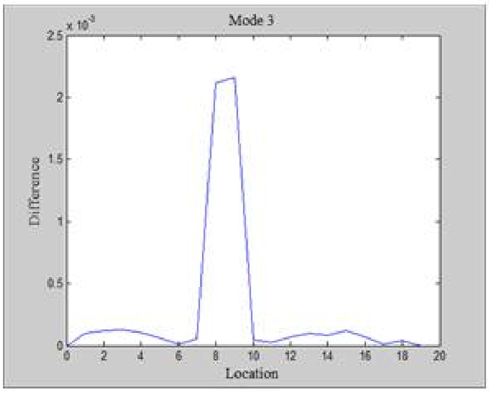


Figure 6: Mode(4)

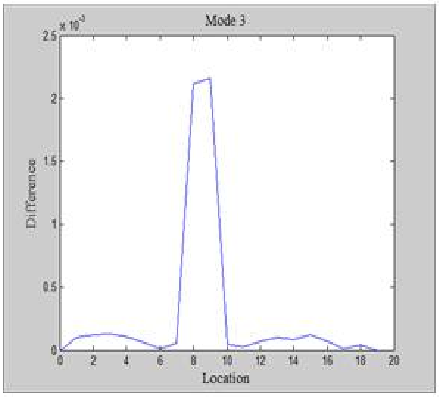
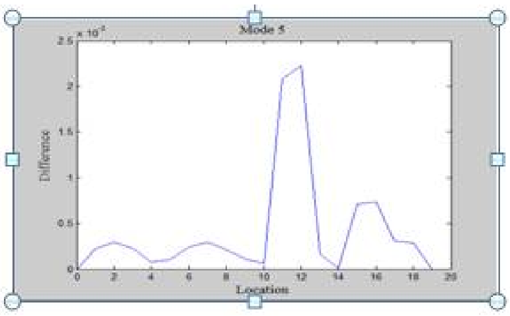


Figure 7: Mode(5)



Case Study 2: Response of a Simply Supported Beam

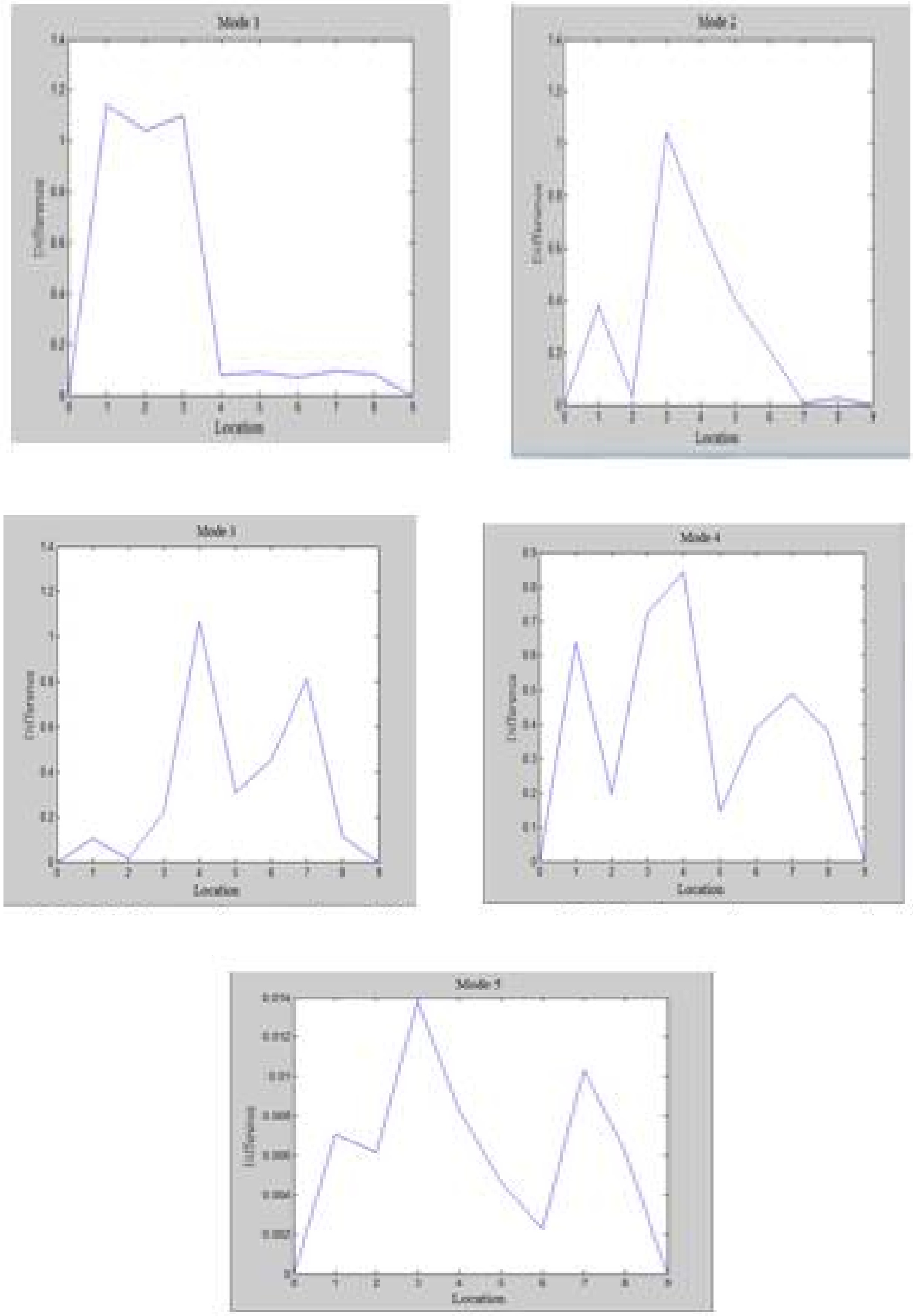
The modal response of a simply supported beam of 10 m length was studied using the method of BSS. The total number of elements in the beam was taken as 11 .The size of the beam was taken as 0.35 x 0.5 m. Sensors were placed at each node except at both end of the beam. The total numbers of nodes were taken as 12 (elements+1). The acceleration data was generated choosing a particular element to be damaged. AR time series model was employed. The damage instant was detected and the modal curvatures for the damaged and undamaged responses were identified. Plots were made for the responses depicting the damage locations. The damage elements chosen include both single and multiple locations. Both single and multiple damage locations were separately studied and plots depicting the damage locations were obtained.

A typical damage matrix is shown below:

Sensor no	Mode(1)	Mode(2)	Mode(3)	Mode(4)	Mode(5)
1	0	0	0	0	0
2	1.138706	0.380216	0.105826	0.637847	0.671196
3	1.043176	0.028849	0.012692	0.195223	0.150423
4	1.099903	1.042628	0.218982	0.721401	1.047296
5	0.079133	0.69517	1.066439	0.842367	0.572295
6	0.090624	0.398386	0.309307	0.14559	0.507427
7	0.072624	0.206608	0.452952	0.387865	0.07453
8	0.095577	0.005728	0.810815	0.488029	1.09175
9	0.082115	0.028056	0.111661	0.377812	0.549462
10	0	0	0	0	0

The damage element was the fourth storey:

Figure 7: Plots Representing the Location of Damage



CONCLUSION

Blind source separation-based damage detection method in conjunction with time-series analysis is proposed in this work. Blind source separation is first utilized to estimate the modal responses using the vibration measurements. Time-series model (AR model) is then employed for one-step ahead prediction of the past measurements. The proposed error index is used to identify the damage instant. Once the damage instant is identified, the damage and undamaged modal parameters of the system are estimated in an adaptive fashion utilizing in the framework of blind source separation. Classical damage detection issues including identification of damage instant, location and severity of damage are addressed using the proposed method. Case studies include the study on the modal responses of a 20 storey shear building and a 10 m span simply supported beam. The results are thus analyzed and plots of the damage locations were made.

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REFERENCES

1. Hoon Sohn, Jerry A Czarnecki, Charles R and Farrar P E (2000), "Structural Health Monitoring Using Statistical Process Control", *Journal of Structural Engineering,* Vol. 126, pp. 1356-1363.
2. Kuroiwa T and Iemura H (2008), "Vibration-Based Damage Detection Using Time Series Analysis", *Earthquake Engineering*, Vol. 12, pp. 12-17.
3. Michael L Fugate (2001), "Vibration-based damage detection using Statistical process control" *Mechanical Systems and Signal Processing,* Vol.15, No. 4, pp. 707-721.
4. Nair K K, and Kiremidjian (2003), "Application of time series analysis in structural damage evaluation", *Proceedings of the International Conference on Structural Health Monitoring*, pp.14-16.
5 Ruigen Yao and Shamim N Pakzad (2011), "Statistical Modeling Methods for Structural Damage Identification", Vol. 8, pp. 25-26.
6. Sadhu A and Hazra B (2013), "A novel damage detection algorithm using time-series analysis-based blind source separation", *Shock and Vibration,* Vol. 20, pp. 423-438
7. Zhang Q W (2007), "Statistical damage identification for bridges using ambient vibration data", *Computers and Structures*, Vol. 85, pp. 476-485